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DEMAND SIDE MANAGEMENT IN THE SMART GRID

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DEMAND SIDE MANAGEMENT IN THE SMART GRID

présenté par: COSTANZO, Giuseppe Tommaso
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M. SAVARD, Gilles, Ph.D., membre

À mes très cher grand parents
Angela, Tomaso et Giuseppe
qui n'ont pas vécu assex pour voir ce memoire.

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RÉSUMÉ

L'objectif du présent projet est de développer des solutions pour améliorer l'efficacité énergétique dans les réseaux électriques. L'approche adoptée dans cette recherche est basée sur un concept nouveau dans le Smart Grids (réseaux électriques intelligents), l'optimisation du Demand/Response, qui permet la mise en œuvre de la gestion autonome de la demande de énergie pour une grande variété de consommateurs, des les maisons à les bâtiments, usines, centres commerciaux, les campus, les bases militaires, et même les micro-réseaux.

La première partie de cette thèse présente le thème de la Smart Grid et évalue l'état de l'art par rapport aux portées du projet. Ensuite, nous introduisons une architecture pour la gestion autonome de la charge du côté de la demande. Cette architecture est composée par trois couches principales, dont deux, l'ordonnancement en ligne et l'ordonnancement au moindre coût, sont pleinement pris en compte, tandis que la troisième couche, la Demande/Response, est laissé comme une extension future. Une telle architecture tire profit de la séparation des des échelles de temps de la consommation d'énergie, et elle est évolutif et flexible. La deuxième partie de ce projet est axé sur la mise en œuvre de l'architecture proposée dans Matlab/Simulink, après une preuve de concept est donnée par des simulations et résultats expérimentaux.

Mots-clés: programmation optimale de la charge, nivelement de la charge de pointe, Demand-Side Management (DSM) autonome, bâtiments intelligents, Demand/Response, efficacité énergétique.

ABSTRACT

The objective of the present project is to develop solutions to improve energy efficiency in electric grids. The basic approach adopted in this research is based on a new concept in the Smart Grid, namely Demand/Response Optimization, which enables the implementation of the autonomous demand side energy management for a big variety of consumers, ranging from homes to buildings, factories, commercial centers, campuses, military bases, and even micro-grids.

The first part of this thesis presents the topic of the Smart Grid and assesses the state of the art with respect to the scopes of the project. Afterward, we introduce an architecture for autonomous demand side load management composed of three main layers, of which two, online scheduling and minimum-cost scheduling, are fully addressed, while the third layer, Demand/Response, is left as future extension. Such architecture takes advantage of time-scale separation of energy consumption. It is scalable and flexible. The second part of this project is focused on the implementation of the proposed architecture in Matlab/Simulink and a proof of concept is given through simulations and experimental results.

Keywords: Optimal load scheduling, Peak-load shaving, Autonomous Demand-Side Management (DSM), Smart Buildings, Demand/Response, Energy efficiency.

CONDENSÉ EN FRANCAIS

Introduction

Le réseau électrique intelligent (the Smart Grid) est une technologie émergente dans le domaine des systèmes de production, transmission et utilisation de l'énergie. Ceci aura un impact profond sur la vie de nombreux consommateurs au cours de ce siècle. Les progrès dans ce domaine apporteront également de multiples avantages économiques, sociaux et environnementaux dans notre société. Pour faire face à ce défi, non seulement la communauté scientifique mais aussi de nombreux partenaires industriels et publics prennent des mesures pour moderniser les infrastructures du réseau électrique et des technologies connexes, afin d'assurer la production et la distribution d'énergie dans le siècle prochain.

Cette recherche a pour but d'apporter des instruments pour une gestion efficace de l'énergie électrique, qui peut être étendue à différents niveaux de la Smart Grid (comme à la maison, dans le bâtiment ou le district). Ce travail se concentre en particulier sur l'optimisation des charges électrique de consommateurs en vue de favoriser l'utilisation des sources renouvelables dans les réseaux de distribution et de permettre une consommation intelligente de l'énergie.

Les Réseaux Électriques Inteligents

D'après la définition de F.L. Bellifemine, le *Smart Grid* est *"un réseau électrique capable d'intégrer toutes les actions des clients et des producteurs branchés au fin de distribuer l'énergie électrique de manière efficace, durable, à bas prix et en toute sécurité."*[Bellifemine, F.L. et al. (2009)]. Le mot Smart Grid exprime *"une vision combinée qui utilise le réseau d'information pour améliorer le fonctionnement du réseau d'électricité."*[V. Pothamsetty and S. Malik (February 2009)].

Par rapport aux réseaux électriques traditionnels, la Smart Grid peut gérer des flux bidirectionnels d'électricité et d'information. Cette caractéristique joue un rôle clé pour une participation active des consommateurs dans le marché énergétique. L'union entre les infrastructures du réseau électrique et des technologies disponibles dans le domaine des communications permettra la programmation de la consommation, la prévision de charge et le nivellement des pics de charge dans le réseau de distribution ce qui améliorera considérablement l'efficacité du réseau.

Le contrôle des charges du consommateur et son interfaçage vers la grille visent à une amélioration de l'efficacité énergétique. Les sujets d'intérêt de ce domaine comprennent:

- Compteurs intelligents: appareils capables de mesurer des grandeurs différentes en temps réel, d'analyser les données et de les rapporter grâce à des systèmes de communication. Ces dispositifs peuvent être intégrés dans une structure de mesure avancée (Advanced Metering Infrastructure) qui fournit des types d'informations différents et de services pour les clients et les fournisseurs d'énergie.

- Appareils intelligents et domotique: ce secteur concerne la modernisation des appareils électroménagers afin de communiquer et ajuster leur fonctionnement aux besoins des usagers en vue d'optimiser la consommation électrique.

- Gestion dynamique et prévision des consommations: ceci permettrait aux clients une meilleure programmation des activités à domicile dépendament du prix de l'énergie. Pour les fournisseurs, en revanche, cette gestion serait extrêmement utile pour l'optimisation de la production de l'énergie.

- Intégration et optimisation des sources d'énergie renouvelables: l'augmentation des centrales de génération distribuée et la forte pénétration des ressources renouvelables dans le marchée énergétique, représente un grand défi pour l'augmentation de la stabilité du reseau et de l'efficacité ainsi que la baisse des émissions de CO_2. Par ailleurs, la participation des clients dans le marché énergétique à travers la coopération des pays, l'intégration des nouvelles technologies, la standardisation, l'augmentation de fiabilité et les nouveaux investissements dans les pays de l'Union Européenne et de l'Amérique du Nord sont facteurs importants pour la construction des Smart Grids.

- Optimisation du "demand/response" et la tarification dynamique de l'énergie, qui permettra un contrôle intelligent des charges selon le prix de l'énergie. De cette manière les clients peuvent régler leurs consommations en temps réel selon le tarif.

- Cyber sécurité: aujourd'hui les réseaux électriques peuvent offrir un bon niveau de sécurité informatique contre les attaques des pirates informatiques grâce à des standards et des réseaux de communication dédiés, ainsi que des systèmes de contrôle redondantes. Il ne reste qu'à vérifier si le passage au Smart Grid rendra les pays plus vulnérables aux attaques informatiques.

Une architecture pour la gestion automatisée de la charge électrique

La distribution intelligente de l'énergie serait une application directe des compteurs intelligents. Ces premiers permettront une consommation optimisée en coordonnant tous les dispositifs afin de minimiser les coûts. Commerce et tarification de l'énergie en temps réel, choix éco durables, gestion du CO_2, ne sont que quelques applications possibles dans le domaine de l'automatisation des bâtiments.

L'architecture du système proposé pour le DSM (Demand Side Management) consiste en trois niveaux principaux (figure 0.1): Admission Control (AC), Load Balancing (LB) et Demand/ Response Manager (DRM). AC est le niveau inférieur qui interagit avec les appareils intelligents pour le contrôle de la consommation en temps réel. Dans ce travail, l'approche adoptée pour le contrôle des appareils utilise des stratégies de planification en ligne inspirée de la technique d'ordonnancement dans les systèmes informatiques embarqués (voir, par exemple, [Buttazzo (2005)] et les références citées).

L'introduction d'un modèle d'appareil électroménage générique permet la planification des activités et de la consommation de façon systématique. Le niveau supérieur, le DRM, est l'entrée du système DSM et représente une interface à la Smart Grid. Il est possible de mettre au point plusieurs stratégies de tarification de l'énergie comme la tarification de pointe critique ou la tarification de temps d'utilisation. Le niveau intermédiaire (LB) coordonne les activités du niveau supérieur (DRM) et inférieur (AC) et équilibre la consommation à travers un algorithme qui répartit la charge en minimisant les couts énergétiques. L'équilibrage de charge entraîne un problème d'optimisation qui sera résolu avec les instruments de la programmation linéaire. Le LB fournit également au DRM des informations importantes concernant le taux de rejet des demandes, un paramètre de performance requis pour la gestion effective du Demand/Response. Les charges électriques sont classées selon leurs caractéristiques intrinsèques en trois catégories différentes:

1. **La charge de base** est une consommation électrique requise nécessaire des appareils qui sont activés immédiatement à n'importe quel moment ou pour le maintien dans l'état de "stand by". Cette catégorie comprend l'éclairage, les ordinateurs, les systèmes de communication et tous les autres dispositifs dont la valeur commerciale ne permet pas l'installation d'une intelligence comme le sèche cheveux, le toaster ou le chargeur.

2. **La charge régulière** est la puissance requise par les électroménagers qui sont toujours en fonction pendant une longue période de temps, comme la climatisation, le chauffage ou le réfrigérateur.

3. **La charge de pointe** est propre aux appareils dont le cycle d'opération a une durée fixe. Cette catégorie comprend, par exemple, le sèche linge, le lave-vaisselle, la machine à laver ou le four. Souvent les pics d'absorption sont causées par l'accumulation des charges de pointe avec des charges régulières. Par conséquent, une gestion attentive de la charge de pointe devient fondamentale pour la réduction des coûts de l'énergie.

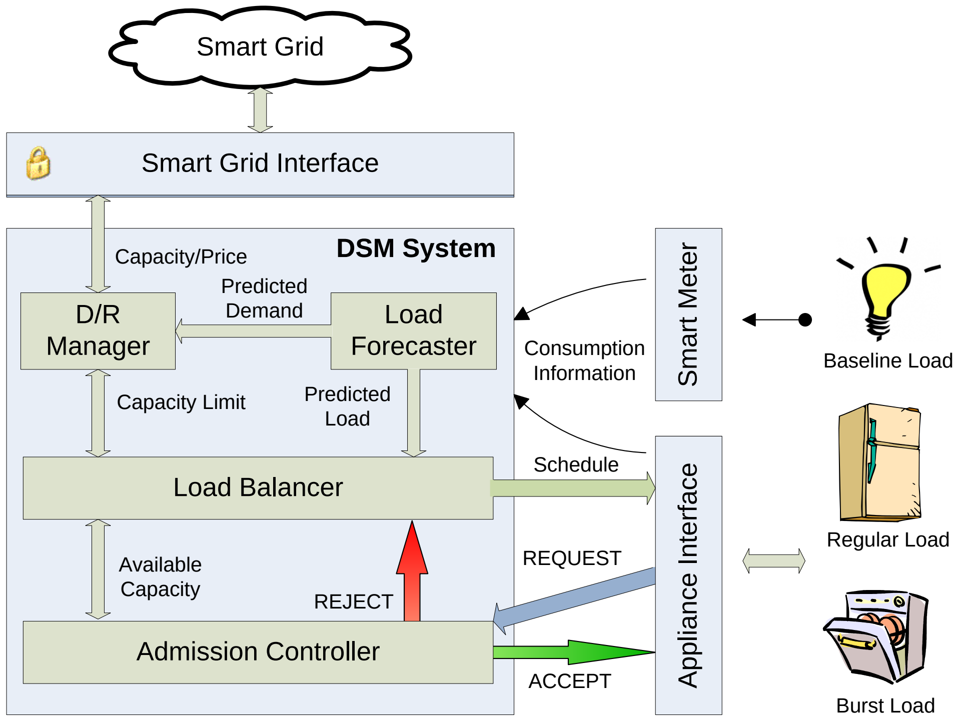

Figure 0.1 Architecture proposé pour le systéme de géstion des charges.

Dans cette recherche, les appareils électroménagers intelligents sont supposés être capables de communiquer avec le gestionaire d'énergie et de garantir un contrôle adéquat au niveau des dispositifs. La communication au sein du système DSM doit être suffisamment fiable et les retards doivent être négligeables par rapport à la dynamique des appareils. Le réseau de communication se base sur des technologies filaires et sans fil [Drake *et al.* (2010),Li et Sun (2010)] et utilise des interfaces spéciales pour communiquer avec les électroménagers intelligents.

Une telle architecture se base sur la division temporelle des dynamiques liées à la gestion des charges domestiques.

Mise en œuvre avec Matlab/Simulink

Cette section présente la mise en œuvre de l'architecture proposée avec Matlab/Simulink, ainsi que des études de simulation pour le système de gestion des charges résidentielles. Le schéma Simulink du système envisagé est montré dans la figure 0.2, où chaque composant peut être facilement identifié dans l'architecture présentée à la section du DSM (sec. 3.2). Notez que, même si dans la simulation les appareils sont représentés par des modèles simplifiés, l'architecture proposeé dans cette recherche est conçue indépendamment de la précision du modèle des appareils. Les performances de la gestion de la charge dans l'implémentation réelle seront effectivement influencées par les modèles des appareils. La période de simulation

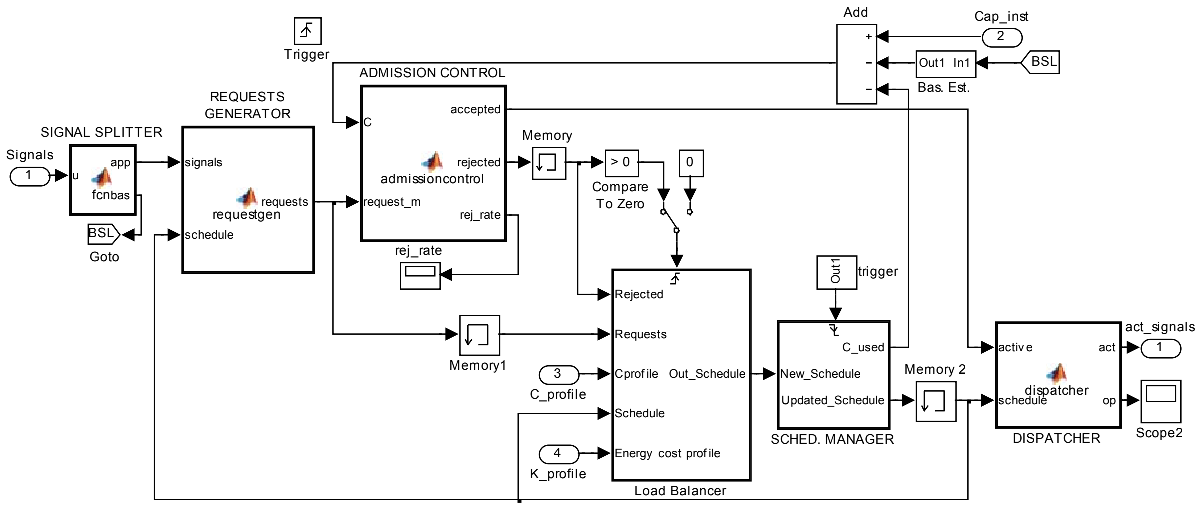

Figure 0.2 Scéma Simulink de l'Home Energy Manager

est normalisée à 100 unités de temps qui peuvent être étendues ou réuites en fonction du comportement des appareils dans un environnement d'application réelle. Les dynamiques thermiques des appareils sont fixées pour représenter un comportement plausible dans l' échelle de temps envisagée.

La configuration comprend trois charges régulières: les chauffages dans deux chambres et le réfrigérateur, alors que les trois charges de pointe sont la machine à laver, le lave-vaisselle et la séchoir. La charge de base est modélisée comme une consommation d'énergie constante dans un laps de temps donné (20 unités de puissance pendant 20 unités de temps).

Les appareils intelligents sont modélisés avec le Stateflow Toolbox$^{\text{TM}}$de Simulink et chaque appareil est en mesure de définir la quantité d'énergie nécessaire pour accomplir sa tâche. Une telle information permet au système d'équilibrage de charge (LB) de calculer le temps restant nécessaire pour compléter chaque tâche. La valeur heuristique pour des charges régulières est linéarisée entre 0 et 1 à l'intérieur des limites supérieures et inférieures des zones de confort, tandis que pour les charges de pointe ce valeur est calculées de façon lineaire envisageant le temps restant pour amorcer. Le modèle d'appareil est complété par le couplage de la machine à états finis dans la figure 3.5 avec l'interface de communication présentée dans la figure 4.4.

Le bloc de Contrôle d'Admission (Admission Control) reçoit deux informations: demandes provenant des charges intelligentes et la capacité disponible à chaque période. De cette manière l'AC permet de démarrer une série d'appareils dont la consommation totale respecte la limite de charge. Les demandes sont classées selon la valeur heuristique décroissante et sont fournie à l'algorithme de contrôle d'admission. Notez que les tâches non-préemptives ne seront pas arrêtées jusqu'à ce qu'elles soient terminées. Par contre, chaque fois que l'AC est invoqué, les tâches préemptives pourraient être interrompues en faveur de tâches avec une priorité plus élevée.

Le Load Balancer est implémenté comme une fonction Matlab imbriquée (embedded function) sur Simulink et il est invoqué dans la simulation comme une fonction extrinsèque. L'outil de programmation entier binaire est utilisée pour résoudre le problème défini dans la section 3.5. Cette fonction utilise l'outil Matlab de programmation linéaire (PL) avec un algorithme de recherche de solutions basé sur la technique de branch-and-bound. La stratégie de recherche de nœud est basée sur la recherche en profondeur (depth-first search), qui choisit un nœud enfant au niveau inférieur dans l'arbre si ce nœud n'a pas déjà été exploré. Sinon, l'algorithme se déplace vers le nœud d'un niveau supérieur dans l'arbre et poursuit la recherche [The Mathworks Inc. (2011)].

Le répartiteur de tâches (dispatcher) est activé toutes les 10^{-2} unités de temps et fournit aux appareils les signaux de contrôle pour l'opération. Toutes les dix unités de temps le gestionnaire du plan (Schedule Manager) fournit au répartiteur la liste d'opérations pour les dix unités de temps suivantes.

Résultats de simulation

Consommation d'énergie sans nivellement des charges. Dans la première simulation, toutes les demandes arrivent simultanément et aucune limite n'existe sur la consommation (limite de capacité). Nous pouvons alors observer dans la figure 3(a) que la consommation d'énergie de pointe atteint 120 unités. L'état d'activation des appareils pendant l'opération aussi bien que l'évolution de la température des trois charges régulières sont indiqués respectivement dans les figures 3(c) et 3(d).

Nivellement des pointes de charge par le contrôle d'admission. Le deuxième cas est conçu pour vérifier la performance du système DSM en utilisant uniquement la planification en ligne des opérations (c'est à dire au seul moyen du contrôle d'admission). Dans la simulation, la limite de capacité est fixée à 40 unités, ce qui correspond à 1/3 de la consommation électrique maximale de pointe. On peut voir dans la figure 4(a) que le pic de puissance consommée a été nivelé afin de respecter la contrainte sur la capacité. Cependant, on peut remarquer dans la figure 4(c) que les trois délais relatifs aux charges de pointe (40, 40 et 70 unités de temps) n'ont pas été respectés. Cette problématique est causée par l'algorithme de gestion en ligne, qui est sous-optimal.

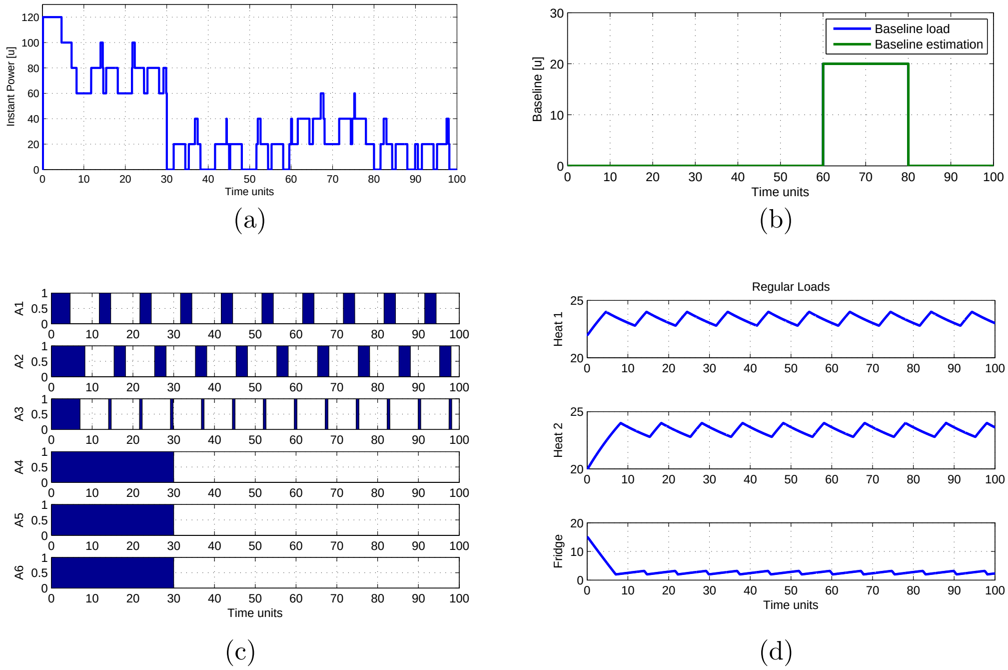

Figure 0.3 Opération sans gestion de la charge: (a) consommation totale; (b) états d'activation des appareils eléctroménagèrs; (c) évolution de la température; (d) charge de base.

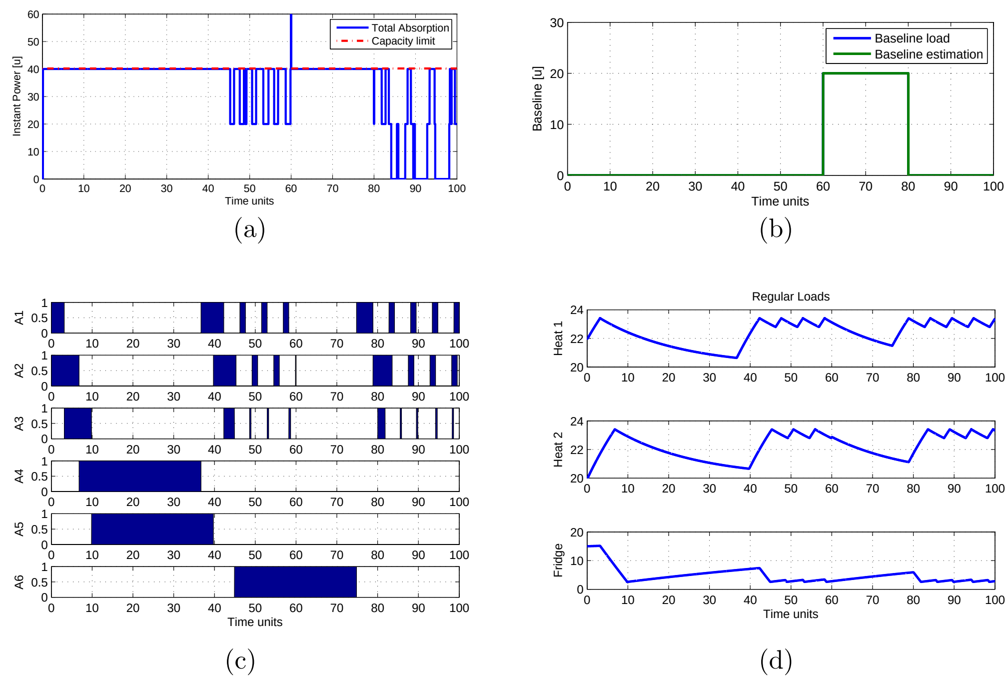

Figure 0.4 Gestion de la charge par contrôle d'admission: (a) consommation totale; (b) charge de base (c) états d'activation des appareils eléctroménagèrs; (d) évolution de la température.

Nivellement des pointes par le contrôle d'admission et l'équilibrage de charge. Nous allons maintenant montrer que, en utilisant l'équilibrage de charge, le système est capable de gérer les charges de pointe en respectant les delais fixés et, par conséquent, il produit un ordonnancement optimal. La figure 5(a) confirme que la contrainte sur la capacité limite à été respectée. L'état d'activation dans la figure 5(c) montre que les contraintes sur les délais pour les charges de pointe ont été respectées.

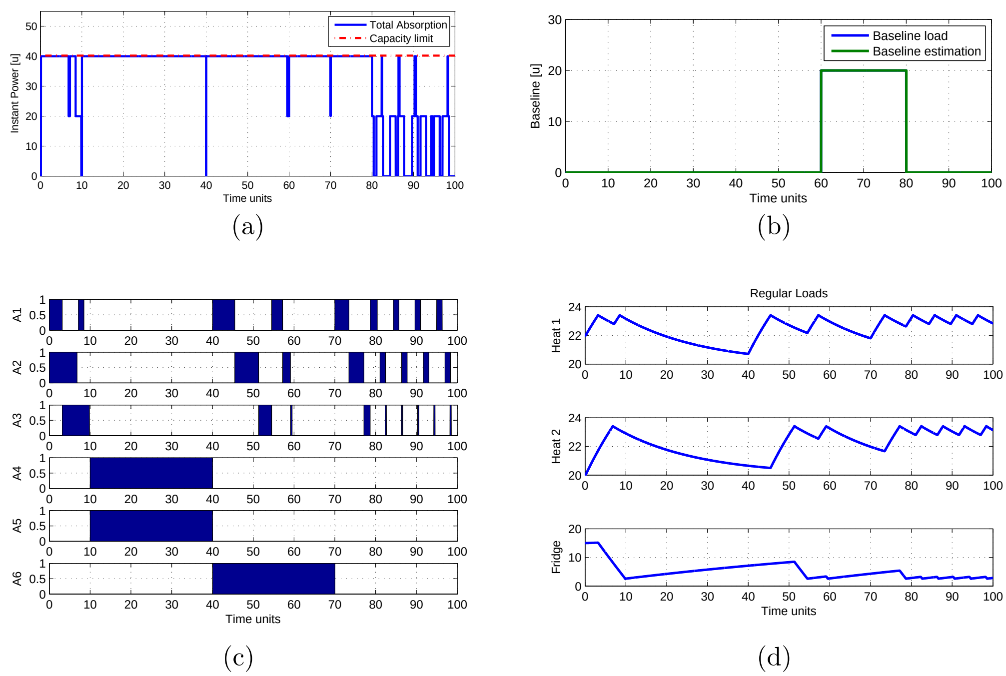

Figure 0.5 Gestion de la charge par contrôle d'admission et équilibrage de charge: (a) consommation totale; (b) charge de base (c) états d'activation des appareils eléctroménagèrs; (d) évolution de la température.

Étude expérimentale

Dans cette section nous présentons les résultats obtenus dans la configuration expérimentale à RISO DTU. Cette institution, grâce au projet Derri, a donné accès à tous les équipements nécessaires pour compléter les expériences afin de tester l'architecture développée dans le cadre de cette recherche.

Fonctionnement sans gestion de la charge. Cette expérience vise à montrer comment la superposition de la charge régulière cause des pics d'absorption élevés. Pendant la phase d'initialisation du système de contrôle, comme la température de nombreuses chambres se trouvent hors de la zone de confort, un grand nombre de demandes arrivent au même moment. Puisq'il n'y a pas de limitation sur la consommation de puissance, l'AC accepte toutes les requêtes reçues. L' évolution de la température et les zones de confort relatives aux chambres de 1 à 8 (R1, R2,..., R8) sont indiquées dans les figures 6(a) et 6(b). La consommation totale de puissance, la température extérieure et la température interne du réfrigérateur sont présentées dans la figure 6(c).

Gestion de la charge via le contrôle d'admission. Dans l'expérience rapportée ici, l'AC utilise une limite de capacité constante de 3000W pour la gestion des charges, en utilisant l'algorithme présenté dans la section 3.4.

Nous pouvons observer dans les figures 7(a) et 7(b) que la température est maintenue dans la zone de confort dans toutes les chambres grâce à l'air conditionné. Tandis que le surchauffage des salles sans air conditionné est, par fois, inevitable pendant la journée. La température interne du réfrigérateur est maintenue malgré le fait que les pics d'absorption ont été réduits (figure 7(c)). Toutefois la limite de capacité de 3000W n'est pas toujours respectée. En fait, le point culminant est mesuré à 4520W et est causé par différents facteurs, tels que l'incertitude sur les modèles des appareils (qui est basé sur la consommation de puissance nominale) et les variations de la charge de base.

Néanmoins, le système DSM montre ses avantages en termes de réduction des pointes de consommations. La réduction est de 61,8% sur la consommation nominale (de 11860W à 4520W), de 54,5% en ce qui concerne le pire cas de consommation expérimentale (au début de l'expérience, à partir de 9940W à 4520W), et de 37,2% pendant le fonctionnement en régime permanent (de 7200W à 4520W).

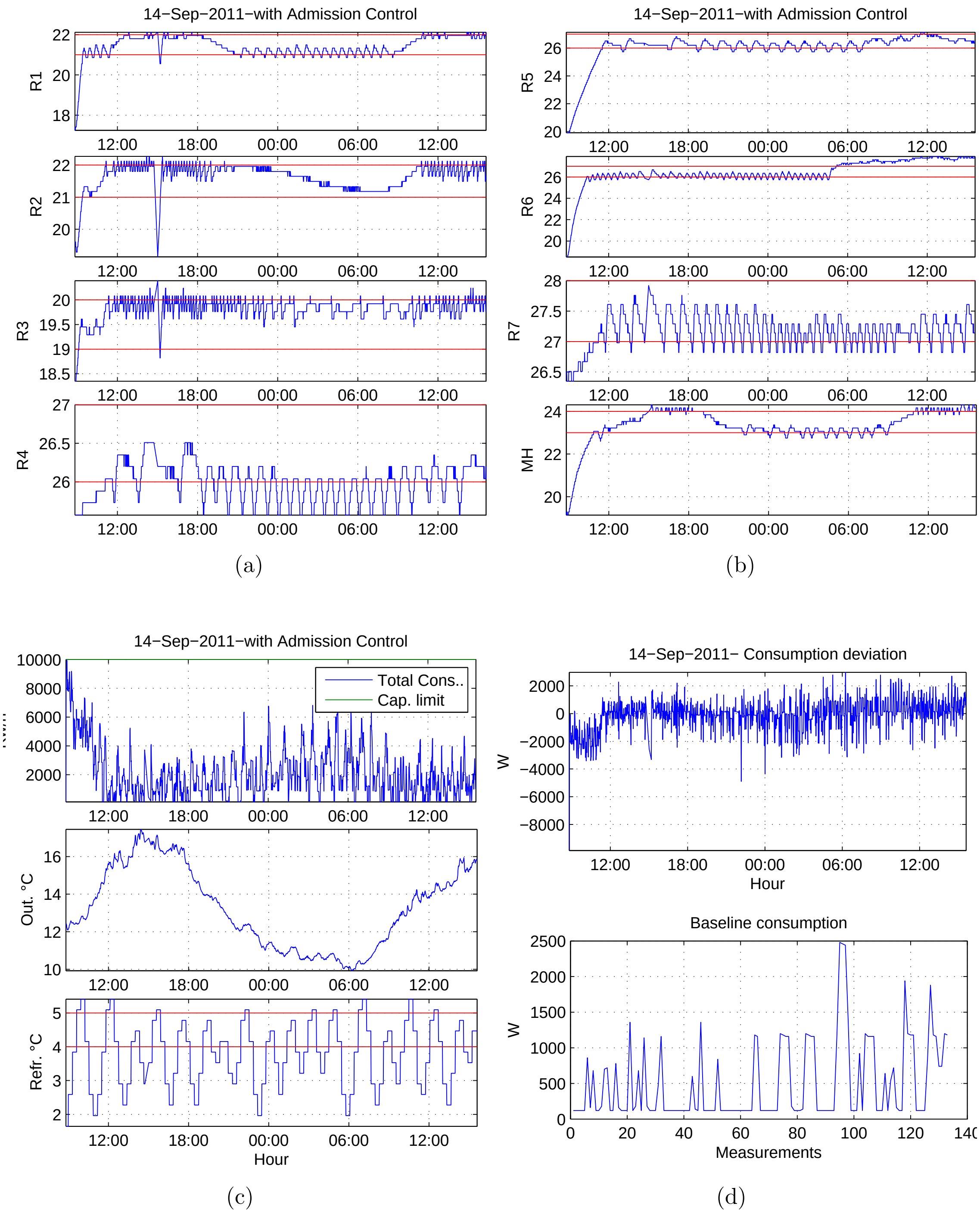

Figure 0.6 Opération sans gestion de la charge (EXP): (a) Évolution de la température dans les chambres de 1 à 4; (b) évolution de la température dans les chambres de 5 à 8; (c) température extérieure et température interne du réfrigérateur; (d) écart de consommation et charge de base.

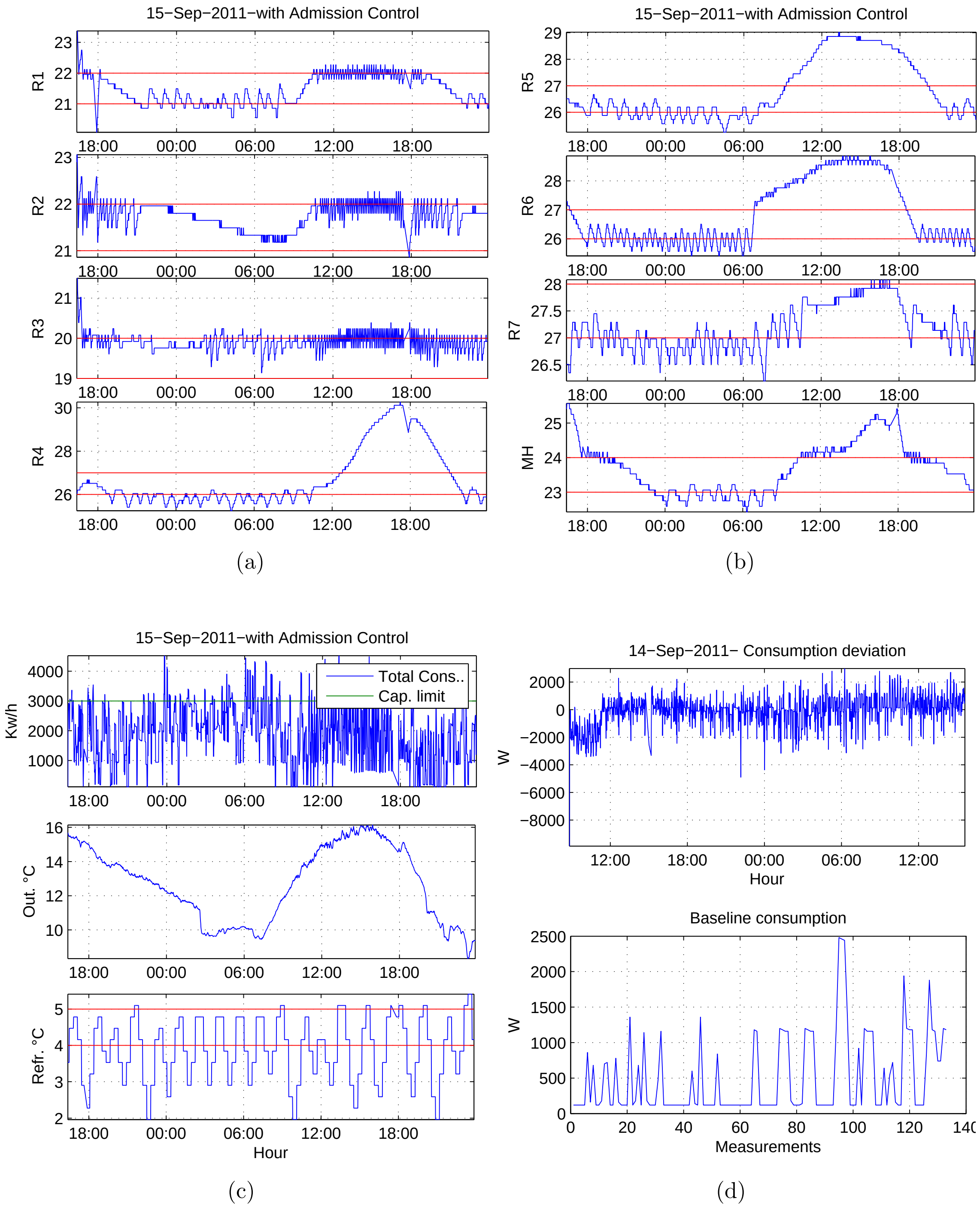

Figure 0.7 Gestion de la charge par contrôle d'admission: (a) évolution de la température dans les chambres de 1 à 4; (b) évolution de la température dans les chambres de 5 à 8; (c) température extérieure et température interne du réfrigérateur; (d) écart de consommation et charge de base.

Conclusions.

L'architecture proposée est évolutive, flexible et intégrable avec divers algorithmes de contrôle. Ces caractéristiques permettent un contrôle hiérarchique à partir des niveaux plus élevés, permettant ainsi de poursuivre des objectifs plus élaborés en matière de gestion de l'énergie dans les maisons intelligentes, y compris ceux qui peuvent atteindre à long terme des performances optimales.

Les études de simulation et les résultats expérimentaux ont prouvé le bon fonctionnement du concept concernant le système DSM proposé et éclairent ses limites. Par ailleurs l'efficacité du système de nivellement des pointes de charge est liée aux mesures et aux modèles des appareils électroménagers.

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LIST OF ABBREVIATIONS

AC	Access Control
AMI	Advanced Metering Infrastructures
API	Application Programming Interface
DG	Distributed Generation
D/R	Demand/Response
DSM	Demand-Side Management
FSM	Finite State Machine
HAN	Home Automation Network
HEM	Home Energy Manager
HVAC	Heating, Ventilating and Air Conditioning
ICT	Information and Communication Technologies
IrDA	Infrared Data Association
LB	Load Balancer
LEED	Leadership in Energy and Environmental Design
LFM	Load Forecasting Module
OPF	Optimal Power Flow
PHEV	Plug-In Hybrid Electric Vehicle
PLC	Power Line Carrier
PUC	Personal Universal Controller
RES	Renewable Energy Sources
WLAN	Wireless Local Area Network
SAI	Smart Appliance Intelligence
ZNEB	Zero Net Energy Buildings

CHAPTER 1

INTRODUCTION

The scope of this research deals with demand side optimization in the Smart Grid, which is an emerging technology that will affect the structure of power grids by integrating advanced communication technologies. In many countries in the EU and in the United States, coal and nuclear plants provide the majority of energy production [European Commission (2011), Simon et Belles (2009)], while peak absorption is matched by regulation plants and power exchange between grids. Throughout the last two decades, factors, such as increased global energy demand, speculation of fossil fuels, and global warming have generated a high interest in renewable energy sources. Nevertheless, energy sources, such as wind and solar power, have an intrinsic variability that can seriously affect the power grid stability if they account for a high percentage of the total generation.

To face these challenges, the scientific community, as well as many industrial sectors, are taking steps to upgrade electrical network infrastructures and related technologies to ensure energy production and delivery through the next century. In this scenario, Smart Grid technologies interests different actors in the power systems sector such as utilities, transport and distribution companies, customers, equipment manufacturers, services providers, or electricity traders.

Motivation

At the moment, production of solar and wind power is not large enough to threaten the grid stability, but if governments pursue green energy policies, structural and technological updates will be necessary in the next decade. Customers will also participate in conserving the grid stability by adjusting energy consumption contingent on the grid status.

In this context, there is a large interest in funding research in economic fields such as power systems, electronics, mechanics, and information technology.

Research objectives and contribution

This project aims to put forward an original point of view on energy management for the consumption side of the Smart Grid as a tool to support decisions concerning investments in sustainable energy and electricity market policies. The research objective is to address the problems of demand side optimization and propose a system design that can handle this problem autonomously. Such a DSM system enables efficient energy management in Smart Buildings and offers the means for effective load shedding, dynamic energy pricing, users aggregation, and energy trading. Another objective of this research is to maintain the scalability and flexibility of the architecture, so that energy management can be addressed at different levels of the Smart Grid.

The contribution of this research is the harmonization of different scheduling and optimization techniques in a way that can take advantage of the time scale separation of energy requests in dwellings. In this context, the architecture is layered and each module operates in different time scales and with different triggering policies. The whole system has three main layers, which deal respectively with requests handling at run-time, optimal scheduling, and energy trading. In this way it is possible to manage energy requests and have flexibility with respect to environmental changes, while maintaining a high level of optimality.

We aim to propose such architecture as a self-standing approach for autonomous demand side load optimization, always considering that improvements can be made at every level, refining the algorithms and augmenting the computational capabilities of the system.

Thesis plan

This thesis includes a summary in French, after which is placed the introduction chapter. Chapter 2 introduces the Smart Grid, and presents the technologies that are being assessed to deal with problems facing electric grids in the coming years. The same chapter presents the Smart Grid as the natural evolution of the actual electric grids paradigm in a way that acts as the literature review for this research. Chapter 3 presents the architecture for autonomous demand side load management and a detailed description of the main components of such a system. Chapter 4 sketches out a software implementation of the proposed system and presents case studies from simulations. Chapter 5 reports some experimental results of the proposed system for residential energy management, while Chapter 6 outlines the conclusions and potentially subsequent developments in this field.

CHAPTER 2

DEMAND-SIDE ENERGY MANAGEMENT IN THE SMART GRID

2.1 An introduction to the Smart Grid

A serious event that rose up concerns about the reliability of electric grids in North America was the blackout in August 14, 2003, which affected 55 millions of consumers in the Northeast of United States and in some areas of Canada (see [Schneider Electric corp. (2010)]) causing an economic impact estimated between 7 and 10 billion US dollars [IFC Consulting (Feb. 2009)]. By that occasion, U.S. government realized the necessity and the urgency to upgrade the national energy infrastructures and policies.

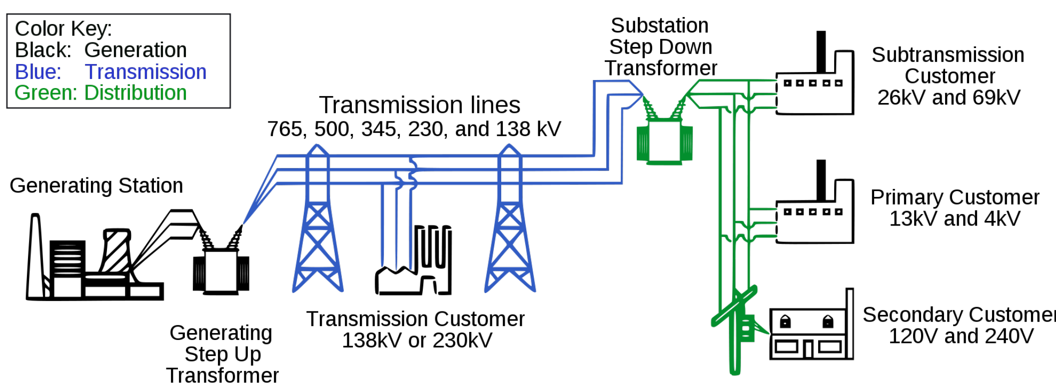


Figure 2.1 : Simple diagram of energy production, transport and distribution grid [1]

The spread of distributed generation plants and the high penetration of renewable resources are putting the existing grids, which were designed to meet market's needs based on the centralized carbon-based production(Fig. 2.1), to face challenges such as increasing the energy transit and efficiency while decreasing carbon emissions. Moreover, the participation of customers in the energy market, the integration of new technologies through standardization and interoperability, the need for high reliability and the new investments in many European Union member countries are important factors leading to the building of Smart Grids in Europe.

Although upgrade of the whole grid can be very costly, its benefit has already been demonstrated by recent achievements in this area. For example, thanks to Distributed Generation

[1] Author: US Department of Energy, under GNU Licence (Wikimedia Commons).

(DG) and Renewable Energy Sources (RES) integration, nowadays it is possible to produce and consume energy within the same area of the power grid, enabling utilities to supply electricity in case of higher demand without upgrading centralized production and increasing transmission capability. Nevertheless, to integrate technologies such as DG, RES, PHEVs and to enable energy conservation in the next decades, utilities have to move toward a new grid architecture, behind which there is a galaxy of different possible developments at both hardware and software levels.

The *Smart Grid* is a vision of the future electric energy system. In [Bellifemine, F.L. et al. (2009)] the Smart Grid is described under a functional point of view as *"an electric network able to integrate all the branched customers' and producers' actions to distribute electric energy efficiently, sustainably, at low operating costs and safely."*. On the same line of thought, Schneider Electric defines the Smart Grid as *"an electric network that can intelligently integrate the actions of all users connected to it: generators, consumers and those that do both, in order to efficiently deliver sustainable, economic and secure electricity supplies"* [Schneider Electric corp. (2010)]. In a business case study of CISCO [V. Pothamsetty and S. Malik (February 2009)] more emphasis is put on roles the information infrastructure plays in such a system by describing the Smart Grid as *"the combined view that uses the information network to enhance the functioning of the electricity grid"*. From the "Power System View," the power grid is an electric network integrating power generation, transmission, and distribution to support costumers' requests.

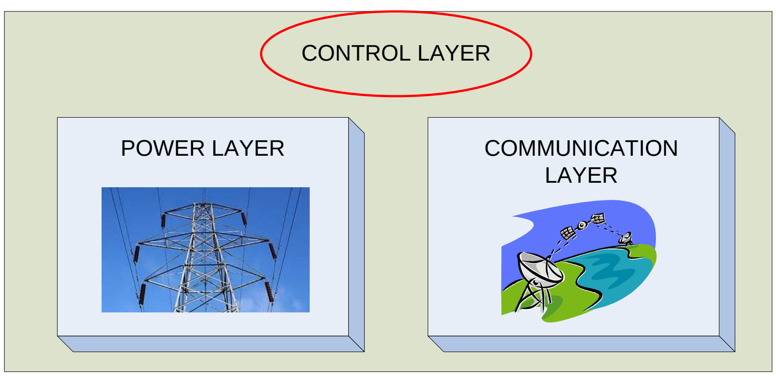


Figure 2.2 : Power, Communication and Control layers.

From "Information System View,"(Fig. 2.2) the operation of such a system is enabled by a communication infrastructure that connects everything from everywhere in the grid. Nevertheless, there is a need of control systems at every level of the grid to make this integration functional, efficient, and effective. A complement of the power and information views is then the "Control System View" based on which a Smart Grid can be seen as a *system of systems* (Fig. 2.3).

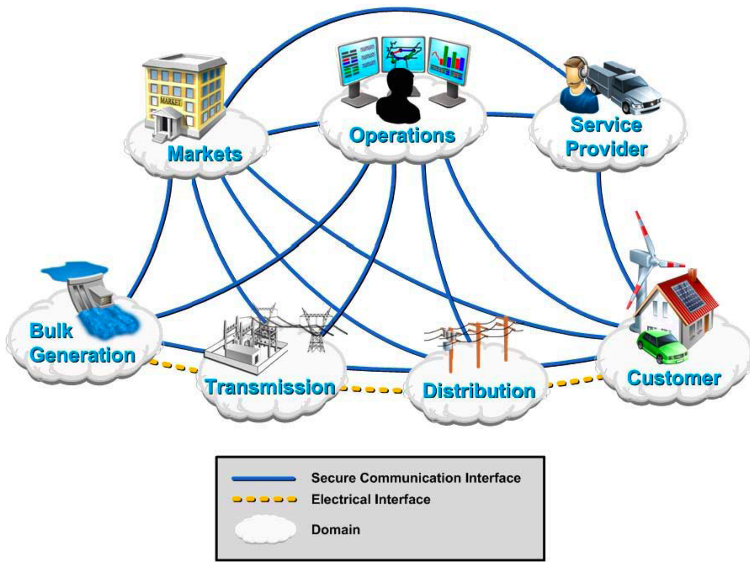


Figure 2.3 : Smart Grid structure. [2]

In accordance with such a viewpoint, J. McDonald pointed out that the Smart Grid is essentially a control problem including [McDonald (2010)]:

- delivery optimization;
- demand optimization;
- asset optimization;
- reliability optimization;
- renewable resources integration and optimization;

This will lead to a more efficient, reliable, and sustainable energy infrastructures which will provide [McDonald (2010)]:

- operational efficiency: with distributed generation, network optimization, remote monitoring, improved assets utilization, and preventive maintenance;
- energy efficiency: with reduced system and line losses, improved reactive load control, peak-load shaving, and accomplishment with governmental policies about energy saving;

[2] ©Copyright:"`http://asjohnson.files.wordpress.com/2010/07/http___nist.jpg`"

- customer satisfaction: as the grid will improve the communication between producers and consumers, the Smart Grid will enable customers self-service;
- CO_2 emission reduction: via demand-side load management and integration of renewable energy sources and PHEVs, and by decreasing the usage of supplementary (and high polluting) support plants.

A distinguishing characteristic of the Smart Grid, if compared to classical electric grids, is the two-way flow of electricity and data (Fig. 2.4). This is a key feature allowing the active collaboration of consumers. In fact, with existing grid infrastructures and currently available IT technologies, one can largely improve energy efficiency of the whole grid by consumption scheduling, load forecasting and peak shaving at consumer side.

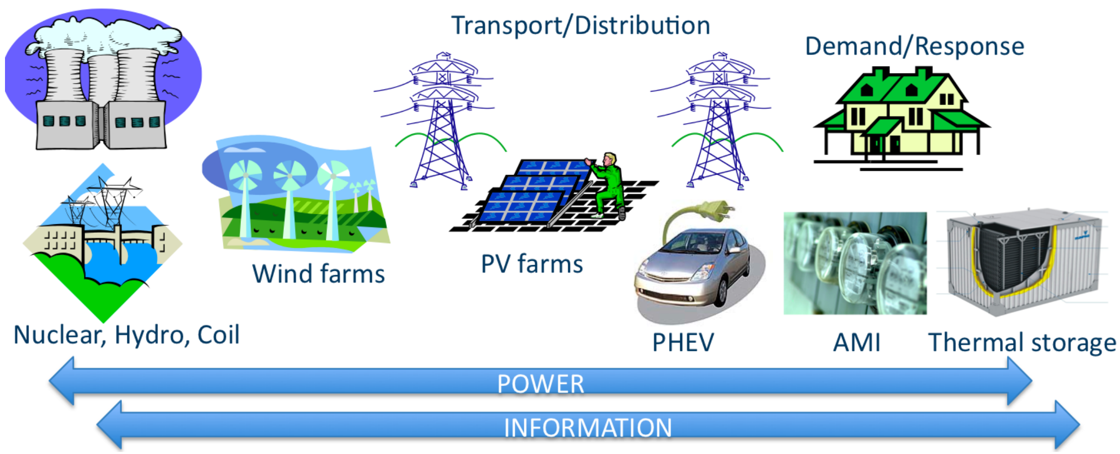


Figure 2.4 : Energy and information fluxes in Smart Grid.

Based on the previous considerations, this research focuses on the control of electric consumption at customer-side and the interface customers and the Smart Grid, in order to achieve a substantial energy efficiency enhancement. Under this scope, the topics of interest include:

- smart metering
- smart appliance and home automation
- dynamic load management and forecasting, peak-load shaving
- integration and optimization of renewable energy sources
- demand/response optimization, energy dynamic pricing

- cyber security

The scope of applications of such practice can range from smart houses to micro-grids, capturing such ones as zero net energy buildings.

2.2 Demand-Side Management (DSM)

A strategy enabling rise of solar and wind supply is to adjust the consumption so as to match the supply. Such practice require communication between customers and utilities, as well as computating capabilities at customer side. In this context, two key technologies enabling demand-side load optimization are [Flynn (2008)]:

- building automation;
- smart metering.

Intelligent energy dispatching among users in the Smart Grid would be a direct application of smart meters and an optimal consumption profile would benefit from a home energy management system (able to manage the devices and perform a cost optimization above operations). Energy pricing, green-power choices, CO2 management, usage pattern monitoring and load side voltage changing detection are only some of the possible applications of building automation one can think about. The presence of distributed generation (solar, wind, biomass, geothermal, cogeneration) and storage facilities (batteries, fuel cells, PHEVs, compressed air) will help to create zero net energy buildings and districts [Kleissi et Agarwal (2010)].

2.2.1 Smart Meters

A *Smart Meter* is a device able to collect measurements of heterogeneous type, analyze data and report readings in real-time. Such devices offer more complex services than automated metering reading (AMR), such as power quality monitoring, remote customer debranching, dynamic service tarification, etc. Such devices (or a less evoluted version of them) can be integrated in an *Advanced Metering Infrastructure* (AMI), providing utilities and customers with different type of information and services (see Fig. 2.5).

Implementing smart metering involves complex communication technologies and may lead to relevant social, economical, and environmental benefits. The social benefits of smart metering is the main argument investigated by Neenan in [Neenan (2008)], who affirms that: *"attributing intelligence, which implies value, to these technologies begs the question on how to measure the gains to realize from making such investments. Not surprisingly, making*

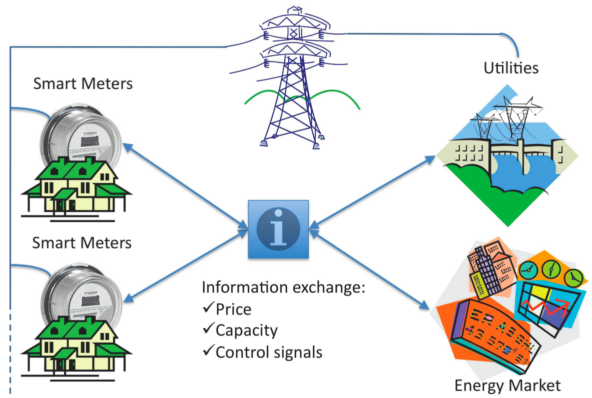


Figure 2.5 : Advanced Metering Infrastructure.

devices smarter is not by itself sufficient to produce benefits to exceed their costs.". This latter argument encompasses the core problem on which is focused the article, making this work to be more focused on the market and social impact rather than on the technological framework of Smart Meters. It is clearly stated that the actions undertaken by customers are generating benefits the evaluation and measure of which "is not without ambiguity." In this context, a framework for characterizing and quantifying social benefits is proposed and the salient aspects such as service reliability enhancement, feedback, demand/response, new products, services and macroeconomic impacts are discussed.

In [S. Karnouskos et al. (2007)] is presented a general overview on Smart Meters, together with an analysis of the funtionalities they should implement and the evolved services they should support. We can imagine a new business model where the internet of "things" may let to trade electric energy, thermal energy, gas and oil, which are seen as commodities in the same marketplace. The smart meters should be connected to the home gateway, that would integrate the home automation network (communication with appliances and devices) with internet (data exchange with utilities). Smart Meters should be multi-utilities (electric & thermal energy and natural gas) and give the support for a deregulated energy market. They should also have a layered structure (Programmable HW, Embedded Middleware, Execution environment API, Services Layer) to support general purpose code implemented by third parties. At the end of the article, the authors present a possible business model for the integration of hardware providers, service providers, and end-users of Smart Meters.

At the Smart Grid level, simple and advanced measurement techniques will help in keeping track of transformers and lines temperature, oil moisture, computing thermo images of electrical devices, and determining the load capability and insulation aging factor. These precautions can reduce by 2.5 times the failure risk, enabling preventive maintenance [Flynn (2008)].

Regarding energy dispatch issues associated with AMI (Advanced Metering Infrastructure, see Fig. 2.5), a mathematical approach for distributed-optimal power-flow computation using smart meters, distributed generation facilities and remote load control, is presented in [S. Bruno et al. (2009)]. Here the possibility for the utilities to reduce customers load with remote signals is investigated. Such a modified OPF (Optimal Power Flow) is capable of taking into account the possibility to buy energy from different distributed providers and deliver it to customers with different needs. The optimization is carried out with respect to the minimization of operating costs for distribution companies and includes two eligible strategies: shedding the amount of energy to ensure the generation/load balance, or evaluate the amount of energy to be bought from distributed generators to balance the demand under the hypothesis of partial load shedding among selected customers. This latter study gives a taste of how the upper layers in the Smart Grid may provide information and control to lower layers as shown in Fig. 2.6.

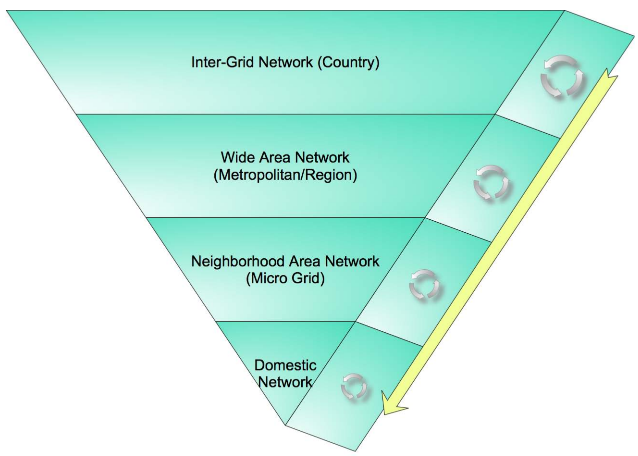


Figure 2.6 : Inner-layer and cross-layer control in Smart Grids.

2.2.2 Demand/Response

Shaping the demand, in order to smooth the load factor during peak hours, can greatly enhance efficiency in power networks and reduce operational costs. One enabling technology for intelligent control from grid to houses is the demand/response approach, in which the energy price is dynamic and customers can adjust the demand in response to supply conditions. Since this latter argument has been widely explored in literature, we refer to [Utilipoint (2010)] for an exhaustive list of references.

In a D/R-based market-clearing price, the energy supply is inelastic and the utility operates the peak shaping basing on a supply function bidding scheme. Basically every customer sends a *supply function* to the utility which, based on the bids of customers, decides the energy price. Therefore the customer is price-taking and commits to shedding or increasing its consumption according to its bid and the energy price [Klemper et Meyer (1989)]. This latter research shows that in a market where customers are price-taking, a global equilibrium that maximizes the social welfare is achieved. Conversely, citing [Lijun Chan et Doyle (2010)], *"in an oligopolistic market where customers are price-anticipating and strategic, the system achieves a unique Nash equilibrium* [3] *that maximizes another additive, global objective function."*

In [Zhong (2010)] a framework for distributed D/R with user adaptation is presented, and techniques assessed in telecommunication network decongestion are applied to the electricity market. Here the energy price depends on the network load and is the only information available to the end user. Such scheme is based on the proportionally fair price (PFP) presented in [F.Kelly et D.Tan (1998)], in which each user declares a willing-to-pay price per unit for his flow. In this sense the network capacity is shared among the users in proportion to the price they pay. In such a model each user tries to maximize a utility function, which depends on the willing to pay price and the capacity request. With such a model, users that pay more, get more capacity share. Such framework is particularly suitable for the DSM architecture proposed in this thesis, since in both studies utilities and users are supposed to be elastic about the energy price.

The above-mentioned Demand/Response scheme requires bi-directional communication between customers and the utility company. Nevertheless, the setting up of an AMI is a task in which costs can be justified only under the hypothesis of active customers participation. In the distribution level of the Smart Grid smart meters are essential units which, in presence of energy management systems, enable demand-side load management. In a Smart Home, for eample, the Home Energy Manager is the middle layer between physical devices and the Smart Grid and, thanks to information on energy price or emergency situations, enables optimal consumption scheduling. Further details on D/R paradigm are presented in Section 3.6.

In such context a big effort is needed from governments in deregulation of the energy market, while the setup of the communication layer and its integration with the electric layer is a utilities' duty. Strategic alliances with telecommunication companies and manufacturers of telecommunication devices are key factors for a successful market entry strategy of Smart Grids.

[3] In game theory, Nash equilibrium (named after John Forbes Nash, who proposed it in [John F. Nash (1951)]) is a solution of a non-cooperative game involving two or more players, in which each player is assumed to know the strategies of the other players. An equilibrium is represented by a set of strategies such that no player has anything to gain by changing only his own strategy unilaterally.

2.2.3 Paradigms of load control

The demand-side load control is an issue that has been studied since the beginning of 90s. Wacks presented in [Kenneth P. Wacks et al. (1991)] the general philosophy of demand-side load management for adjusting energy demand/offer balance. Toward this scope, the energy utilities developed different strategies for load control that are classified as: local control, direct control, and distributed control. Note that all of them need real time access to information from utilities, computer-based intelligence inside houses, home automation communication network and appliances that can reduce their power consumption.

Local control consists in voluntary cooperation of customers to reduce load peaks through taking into account different energy tariffs depending on the daytime. Therefore customers with heavy and not urgent power-consuming activities are encouraged to shift them in peak-off pricing time. Although this strategy is cheap and simple to implement for utilities, it may have limited success since the customers barely understand the kilowatt-hour consumption and related costs of each appliance, in a way that they may not operate efficiently their choices.

Direct control is based on appliances-forced remote switching. After receiving financial inducement, the customers allow the utilities to install in their homes some remote-controlled switches, which would control the load when needed by disconnecting selected appliances. This implies that the air conditioning is turned on and off basing of the outside temperature, daytime and utilities needs. In the same way the water heater would reduce his operation, for example, in the hottest hours of the day.

Decentralized control is a mixed approach relying on customers' cooperation and communication with utilities. The utility has the opportunity to change energy price in real-time according to the energy market and grid load status, while the customer is called to adjust its consumption basing his decisions with respect the tarification. In this scenario home automation takes a fundamental role. As for example, an appliance like dishwasher, connected with the HEM (Home Energy Manager), can provide the customer with the choice to run the cycle when requested or shift it of a certain amount of time with a economic benefit. The article of Wacks concludes with explaining how important is home automation to reach power load control and how should smart appliances be redesigned to this scope. This study, carried out in 1991, summarizes the basic ideas that nowadays are leading toward Smart Homes and Smart Grids.

2.2.4 Smart Appliances and Home Automation Network (HAN)

The home communication network can be implemented with diverse wired and wireless technologies or carrier waves in electrical power lines [Drake *et al.* (2010); Li et Sun (2010)] (Fig. 2.7). In a similar manner, communication between the grid and the DSM system should also be handled by an appropriate interface.

Ideally, the communication system for supporting smart appliances should be based on what is already existing in the house. The technologies that match this vision range from wired PLC-Power Line Communication to diverse wireless technologies, such as Bluetooth, 802.11b (WiFi), ZigBee, IrDA. In [N. Kushiro et al. (2003)], the authors analyze technologies that converge in a residential gateway controller designed for home energy management. Although all technologies carry pro and cons and have different costs, the PLC seems to be the most interesting one. The reason of such preference is due to the reliability and low electromagnetic impact of a wired channel over a wireless one, together with data safety, channel flexibility, and scalability. In Chia-Hung Lien et al. (2008) we find a real implementation of a PLC communication system with an improved Orthogonal Frequency Multiplex algorithm to limit narrow-band noises interfering with the carrier signal. In [Yu-Ju Lin et al. (2002)] and [N. Kushiro et al. (2003)] we find simulations for home communication network based on PLC technology, where security and data consistency issues are also investigated. In [Yu-Ju Lin et al. (2002)] a layered-architecture is proposed to overcome the problems of signals synchronization, data exchange, and channel reliability.

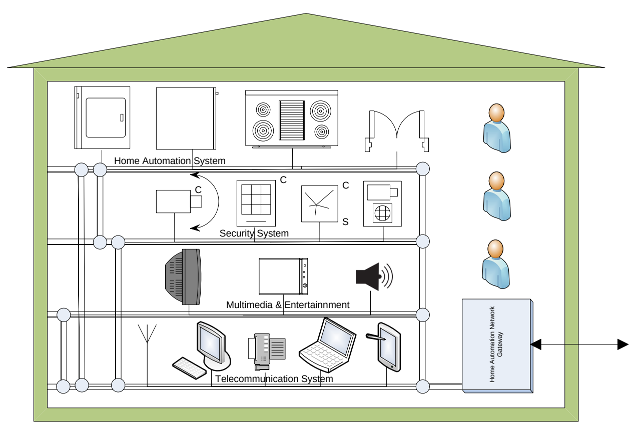


Figure 2.7 : Smart Home Automation Network.

About the issue of how to communicate with appliances, J.Nichols et al. (2002) presents a universal appliances interface that enables to design a controller with different type of interfaces for a wide range of common use appliances. This approach could be adapted in developing "appliance adaptors" for home energy management systems. A self-programming interface is developed for PUC (Personal Universal Controller), which offers to users a complete appliance interface in one single device. In fact, once the appliance is able to receive and send commands (a feature offered by a hardware adaptor and a communication protocol), the PUC can interrogate the appliance about the available functions and generates an intuitive and user-friendly interface. Since the interface is generated basing on the appliance structure, the controller is completely universal. The hypothesis for this scenario is that appliance description must be sufficiently detailed to allow the PUC to generate an adequate interface. An efficient approach to do that is to define a set of state variables, commands, and labels for each appliance and group them in a relational tree. Then, another structure called "Dependency Information" will express all the relations between the appliance state variables, commands, and labels (just think that in a certain state only a subset of the total commands is available). The interesting information found in this work is mainly about the logic behind how to establish communication with appliances and how to define an interface for sending and retrieving data.

2.2.5 Energy demand forecasting

Once established communication between appliances and home energy manager, one of the most interesting features the energy manager may enable for both customers and utilities is the energy consumption profiling. In fact on customer side, such information would allow to better schedule the home activities considering the energy price. On utilities side, it would be extremely useful for the optimization of energy dispatch. As a fact, such topic is one of the most investigated in energy management practice since late 70s. A lot of references can be found in this field and it seems that this problem has been studied using completely different approaches capable to enlighten different aspects and provide solutions accordingly.

Buildings consumption can be divided into electrical and thermal energy. The forecasting process can use top-down or bottom-up approaches, as explained in [Lukas G. Swan et al. (2009)]. The first approach uses data coming from energy suppliers about regional consumption and treats the users as energy sinks; while the second starts from the user level information and goes up in the modeling process to fit the aggregate data provided by energy suppliers. With a top-down approach it is not trivial to disaggregate and forecast the single user consumption because of the merge of historical data with macroeconomic indicators (income, oil price, etc...), technological development peace, and climate [Lukas G. Swan et al. (2009)]. The advantage of this technique lies in its simplicity, which needs only widely available aggregated data. Moreover the historical data give some kind of "inertia" to the model. As drawbacks we find the incapability to catch technological or climate "discontinuities" more than the impossibility to extrapolate single user consumption information. Nevertheless, this approach provides reliable forecasts for long-term energy consumption in wide areas.

It seems that bottom-up is a more practical approach, which comprehends statistical and engineering methods. These approaches use data coming from individual end-users, group of houses or communities in order to extrapolate the model of an entire region or even a country based on the representativeness of the groups or sub-groups of customers used during modelling process. The bottom-up approach use both statistics and engineering methods. Statistical models rely on historical data and use different types of regression to attribute dwelling energy consumption to particular end uses. Once the relationship between end-uses and energy consumption has been established, the model is used to estimate the energy consumption of dwellings representative of the residential stock. Among statistical methods one can find regression, conditional demand analysis and neural networks. For more details, we refer to [Lukas G. Swan et al. (2009)] and references therein.

Engineering methods, instead, try to model energy consumption according to thermal characteristics of houses, consumption profiles of appliances (together with statistical data about market penetration of most common appliances), and behaviour of householders. Among the engineering methods the most relevant are distributions, archetypes, and samples [Lukas G. Swan et al. (2009)]. Archetypes technique consists in classifying the dwellings by vintage, size, house type, etc. Then it is possible to aggregate data and characteristics on appliances to set up the model. The more archetypes are available, the more detailed and adherent to the reality can be the energy consumption estimation for a given region. This latest technique seems to be a suitable choice to extend the Home Energy Manager functionality since the consumption of each appliance is available and only the dwelling characteristics may have to be added.

Common input data for bottom-up approaches include the dwelling geometry, equipment and appliances presence, indoor and outdoor temperatures, occupancy schedule. Such high level of detail is a strong point of the bottom-up approach and gives ability to model technological advances in society. Nevertheless the bottom-up approach could be so detailed that it may underestimate the building energy consumption due to unmodeled illogical householders' behaviour. This latest aspect represents the weak point of engineering methods, the high dependency on householder habits.

It may be interesting to follow an approach that disaggregate the consumption data and classify it by appliances and by day type (weekday, weekend, Sunday, etc.). To this end, Bayesian inference can be performed to set up a prediction model for the dwelling energy

[3] ©The Mathworks Inc., energy usage forecast based on statistic analysis of historical data.

consumption (note that this approach is presented in an article that under review). In [Raaij et Verhallen (1983)], the authors present a behavioural model of residential energy use. Their approach belongs more to psychology science than engineering. However their study is useful to explain and interpret measurement data.

An interesting advancement of the latter approach is presented by A. Capasso in [A. Capasso et al. (1994)], where a user-customized bottom-up approach is developed. The authors merge the statistical and the engineering philosophy together with Monte Carlo-based consumption simulations and show how the model can reasonably predict the household energy need along the day. Although this study has been conducted for the Italian energy market and takes into account Italian householders' lifestyle and appliances ownership, this model is extendable to other countries given the necessary data coming from surveys. Again, this approach may be easily merged with the scheduling approach for home energy management given the HEM can provide appliances use information and statistics as well as home occupancy information.

C.S. Chen in [C.S. Chen et al. (1997)] proposes an approach to define the user load pattern basing on energy consumption measurements that enable to assign a proper energy tarification to the user (statistical top-down method). This would lead to more fair tariffs according to the energy production, transmission and distribution costs. This study has been tailored on Taiwan situation where the carrying factors for time-based energy tariffs are the operational costs of power grid (that depend by the network congestion: peak time).

In summary, energy consumption profiling could be a key feature for a home energy manager, since it may enable the consumption prediction for optimal scheduling and useful data for aggregators in providing ancillary services. Customized billing profile, efficient energy bidding mechanisms, building tenants co-operational models are only few features that an efficient energy profiling system could allow to implement. To reach this objective the bottom-up approach is more attractive than the top-down, and much attention has to be put on modelling the behaviour of householders.

2.2.6 Zero Net Energy Buildings (ZNEBs)

Going one level up, the architecture for energy management in this research work can be extended to smart buildings and micro-grids (Fig. 2.8). One of the most investigated scenarios that smart building technologies would enable is the design of Zero Net Energy Buildings (ZNEBs).

D. Crawlery in [Drury Crawlery et Torcellini (2009)] define a Zero Net Energy Building as a *"building that offset all its energy use from renewable energy sources available within the footprint."* This imply that all this kind of buildings have to reduce their energy consumption at first and then produce on site at least as much energy as they require in a year using demand-side load control and renewable energy technologies, such as daylight heating, advanced HVAC, solar panels, insulation, ground-source heating pumps, ocean water cooling, evaporative cooling, etc. In this article is pointed out that, even though many simulations and studies support the feasibility of a ZNEB, in general the majority of these dwellings achieve to be “near” to the zero-net energy buildings. This is mainly due to optimistic assumptions about the tenants’ lifestyle and the solar radiation level. The penetration of ZNEBs addresses also a stability issue on power networks because, during low solar radiation, the energy peak-consumption in ZNEBs is even more pronounced than in typical buildings [Drury Crawlery et Torcellini (2009)]. Therefore, energy storage facilities should be integrated to limit this problem.

References such as [Iqbal (2004)] and [Kadam (Spring 2001)] offer an economic feasibility point of view of ZNEBs, presenting studies for Newfoundland and Florida regions respectively, while E. Musall et al. (2010) summarizes the state-of-the-art in regulations and active projects on ZNEBs. This latter reference is particularly interesting because it is up to date with the latest information coming from the 2010 European Commission directives on Smart Buildings.

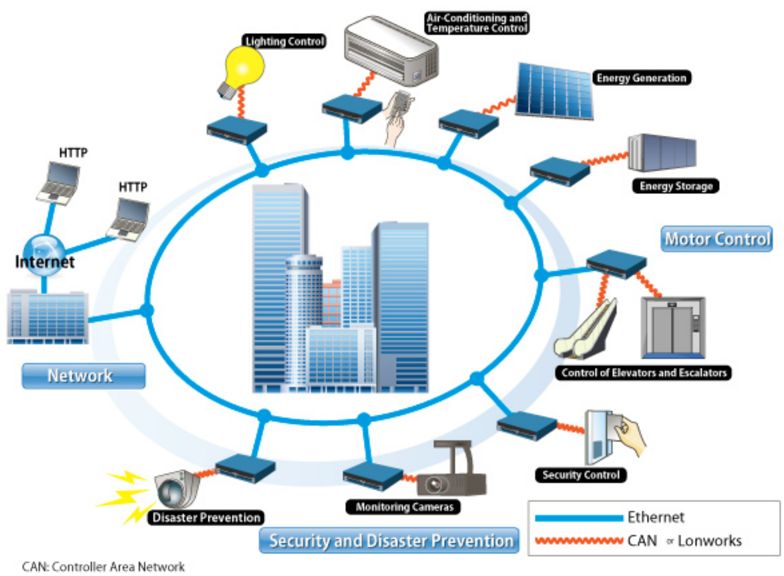


Figure 2.8 : Smart Building concept [4].

[4]©Copyright:”http://www.renesas.com/edge_ol/feature/07/index.html”

2.2.7 Concluding remarks

In conclusion, many challenges regard not only technologies but also standards and regulations about Smart Grids. To this end, the IEEE has established the "IEEE P2030 Smart Grid Interoperability Standards" committee, which *"will provide a knowledge base for understanding and defining smart grid interoperability of the electric power system with end-use applications and loads."* [IEEE-P2030 (2011)]. It is common understanding among utilities and governments that proper actions toward a global standardization in energy production and distribution matter is necessary to make Smart Grids ready-to-implement and cost effective.

CHAPTER 3

ARCHITECTURE FOR AUTONOMOUS DEMAND-SIDE LOAD MANAGEMENT

3.1 Introduction

This chapter presents the architecture for autonomous demand-side load management, a technology that requires communication between utilities and customers. In this context, a working asumption is that communication infrastructure at home and grid level is operative and reliable with respect to the criticality of applications.

DSM enables a win-win situation, where customers adjust their consumption upon economic inducements and utilities avoid grid overloads by spreading the demand during the off-peak time. In this way, the energy demand can actively follow the production and decrease the need of regulation plants and energy storage. Such a technology also affects customers habits in a way that they can:

- save money in energy bills by consuming when electricity is cheaper;
- obtain revenues in offering ancillary services to the grid by the means of DSM and aggregation;
- obtain economical advantages by trading energy with other entities through aggregators;
- actively participate into the environment preservation by assuming a green behavior;
- considerably help in reducing expensive electricity shortages.

From customers point of view, optimizing the energy demand implies to be flexible on the comfort level by accepting to reduce the consumption when requested by the utility. Energy management at customer side is performed by an energy manager, which will have to be completely autonomous, reliable and adaptable to a constantly changing environment.

In our vision, the DSM system takes advantage of the time-scale separation of energy requests and has a layered structure, where each layer has different timing and cope with different objectives of energy management: peak load shaving, costs minimization, tenants comfort and the services offered to the grid. Fig. 3.1 shows the concept design of an energy management system for domestic applications with such a modular structure.

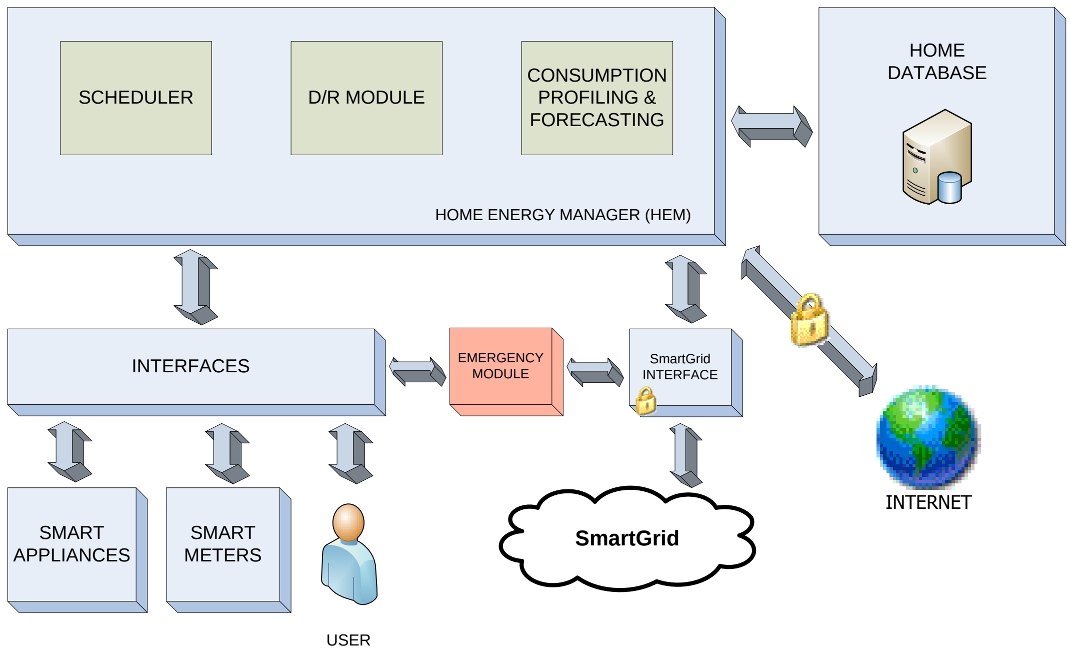


Figure 3.1 : Home energy management system.

3.2 DSM System Architecture

This section presents the architecture for DSM system and explains the functionalities of each module. For instance, domestic energy requests have different time scales, which allow to classifiy loads in three categories based on appliances' intrinsic characteristics:

1. **Baseline load** is the power that referred to those appliances that must be activated immediately at any time or maintained in "stand by" (Fig.3.2(a)). This category includes lighting, entertainments (TV, video games), computing and network devices. Referring to this category also there are devices that are too cheap to embed intelligence. Although baseline load is not controllable, the related appliances can provide their power consumption and operation state to the DSM system via such devices as smart meters. Information on baseline consumption needs to be taken into account when computing the available capacity for admission control and load balancing.

2. **Burst load** is the power consumption of appliances that operate for a fixed time period and are required to start and finish at the given moments. Examples of these appliances include dryer, dishwasher, washing machine, cooking stove, etc. (Fig.3.2(b)). Indeed, peak consumption is mainly created by the accumulation of burst loads with regular loads. Therefore, a careful management of burst load is an issue that has a significant impact on effective peak shaving and energy cost minimization at demand side.

3. **Regular load** is the power consumption required by appliances that are in running state during a long time period, such as house HVAC (Heat Ventilation Air Conditioning), refrigerator, water heater, etc. (Fig.3.2(c)). However, such appliances can be interrupted intermittently, in a way that they represent a particular case of burst loads.

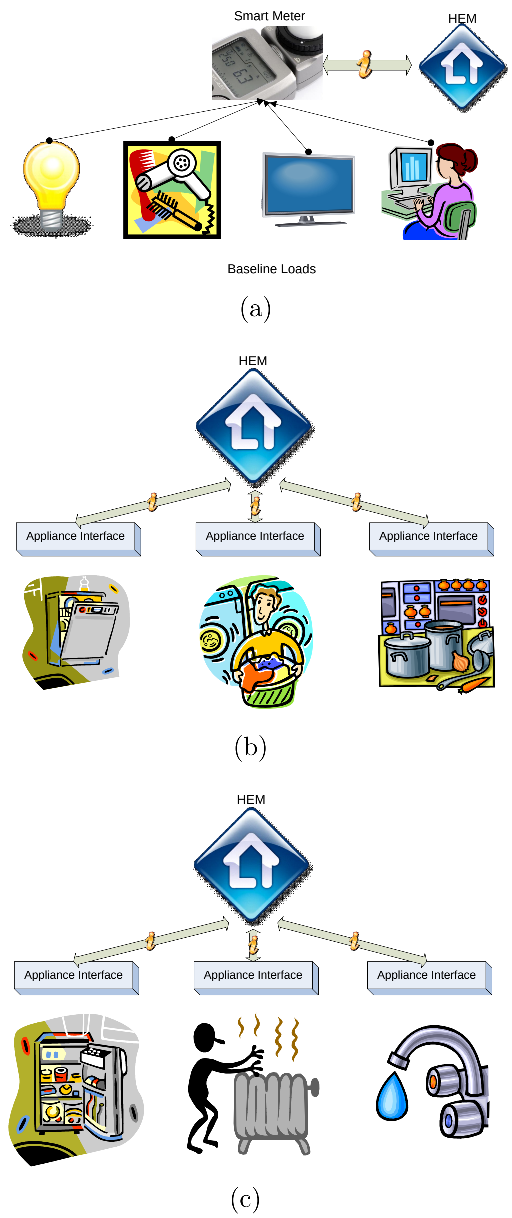


Figure 3.2 Domestic loads classification: (a) baseline load; (b) burst load; (c) regular load.

Figure 3.3 illustrates the DSM architecture, where all the layers can be easily identified as: Admission Control (AC), Load Balancing (LB) and Demand/Response Management (DRM)

+ Load Forecasting (LF). Such architecture contains also adequate interfaces for information exchange with the Smart Grid and with appliances.

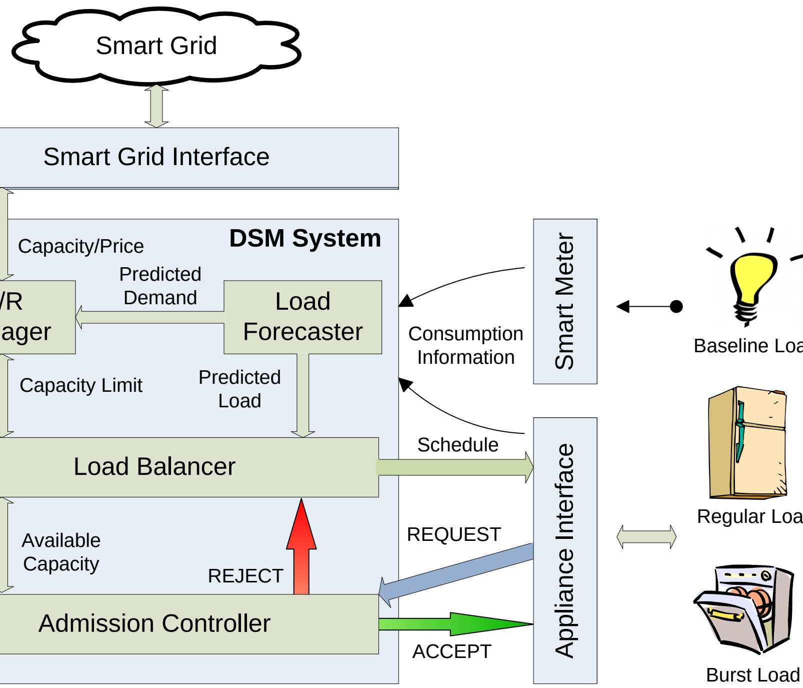


Figure 3.3 Proposed architecture for demand side load management system.

Such an architecture for DSM system takes advantage of the multiple time-scale nature of loads scheduling in Smart Buildings. More precisely, some loads are scheduled at run-time where they are essentially periodic (time-scale of few minutes or shorter). On the other side, handling price bidding and operation scheduling are performed on a much slower time-scale, typically hours, and may be trigged by events such as price change, environment fluctuations, arrival of new requests, etc. With such a load management system it is easier to integrate energy production at distribution level and reduce transport network capacity.

The energy manager can control appliances by means of interfaces, and retrieve information on the dwelling consumption thanks to devices such as smart meters. Appliance interfaces are a middle layer between the physical devices and the energy manager (see Fig. 3.1).

The Admission Control (AC) is the bottom layer of the DSM system and it is deputed to manage at run-time the requests coming from smart appliances and information coming from smart meters. Such module is time-triggered and performs the effective load shedding by accepting a subset of incoming requests and rejecting the rest. In this context, we define the *available capacity* as the maximum power consumption the dwelling is constrained to.

Requests are accepted based on priority, power request and available capacity, in a way that the AC computes the best execution pool at each invocation. Appliances whose requests have been accepted are operated, while appliances whose requests have been rejected are stopped and such requests are passed to the LB.

The Load Balancer (LB) is the middle layer and performs an optimal load scheduling over a wide time horizon by the means of mathematical programming. The LB solves an optimization problem and produces a schedule using information on available capacity, energy cost, load forecasts, tasks' priorities and deadlines. Appliances whose requests have been scheduled, get notified about the best moment to send another request to the AC. If LB retrieves reliable and accurate information on load forecasts, available capacity and energy price therefore the scheduled requests will not be rejected again by the AC. In this context, the LB is triggered by events such as requests rejection, changes on available capacity, energy price profile and load forecasts. In any case, optimization is performed using the maximum information available and the entire schedule is re-compiled in a way to represent always the best solution available.

The LB may not able to provide a feasible solution due to two principal factors:

- tight deadlines;
- lack of capacity / excess of requests.

The first type of failure occurs when the user asks the energy manager to complete a certain task in a time slack which is smaller than the task's proper operation time. In this case, even with availability of sufficient capacity, the DSM system will fail in scheduling some requests and notify the user which constraints need to be relaxed. The second type of failure, instead, is not critical and it is managed by the DRM.

The Demand/Response Manager (DRM) is one of the two modules in the upper layer and represents an interface between the DSM system and the Smart Grid. This module is deputed to trade with the Smart Grid the power capacity and the energy price in view of maximizing tenents benefits and comforts. In this way consumers have freedom to manage and optimize their energy consumption and load control is hidden from other components in the grid. This module can deal with different pricing strategies, such as critical-peak pricing, time-of-use pricing or real-time pricing in order to perfectly negotiate the capacity and the energy price. This module uses feedback information from the Admission Control, Load Balancer, and Load Forecast in order to guarantee an adequate Quality of Service (QoS). The Quality of Service is related to the confort of users, which its formal definition and metrics assessment is still an open issue. In the present research, the comfort is referred to the appliances with internal conditions, as it will be explained in the following section.

The LF is the second module of the upper layer and provides the DRM and LB with load forecasts, which is a crucial information for energy bidding and load balancing. For example, with the aid of load forecasts it is possible to advance the operation of appliances in order to avoid peak-load periods or to fill consumption valleys in the grid. This module may implement different techniques as explained in Section 2.2.5.

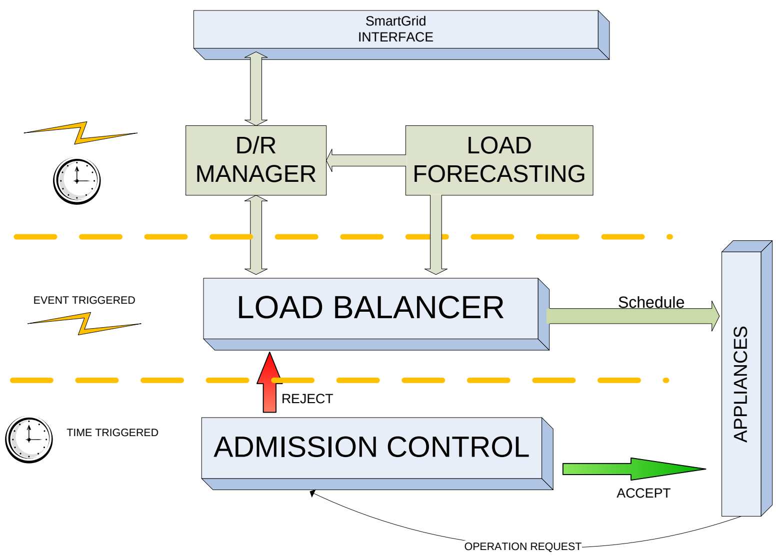


Figure 3.4 Time-scale decomposition and triggering of HEM layers.

In addition to common advantages provided by layered architectures, the proposed framework features the following important properties:

- **Scalability**: the architecture of the proposed system can be used in a vast variety of consumers, ranging from homes to buildings, factories, commercial centers, campuses, military bases, and even micro-grids. The complexity of the components can be very different, while the system structure remains the same.

- **Extensibility**: not only this structure is suitable for conventional electricity load management, but also allows integrating renewable resources and handling energy storage and exchange. A possible implementation is to incorporate diverse objectives and constraints into the model of optimization and scheduling (see [Guan *et al.* (2010)]).

- **Composability**: the mechanism of demand-response management and pricing rules can be implemented by the utilities or energy whole sellers for individual consumers or for group of users. The system can be organized in a hierarchical manner so that the price bidding can be carried out in different levels. In this way, different pricing strategies can be integrated and made to coexist in the same system.

The following sections present the details of smart appliances design, admission control and load balancing. Note that as the design of DRM and LF is beyond the scopes of this research, the related issues will be addressed more thoroughly in future investigation.

3.3 Smart Appliances

In our framework, Smart Appliances are represented with a generic model that enables the development of power consumption scheduling in systematic manner. Ideally, Smart Appliances are enabled for physical control and data communication with the DSM system through generic interfaces, in a way that the DSM system design and implementation is unified. Each appliance interface should handle manual inputs and provide users with operational states, in a way that the appliance can also run in "manual mode". It is assumed that the communication within the system is sufficiently reliable with respect to the criticality level of the services and has negligible delays compared to appliance's dynamics.

In the proposed framework every appliance is represented by a finite state machine (FSM), as shown in Fig. 3.5, regardless the type of load. It is assumed that the appliance manufacturer provides the means for operation control and monitoring of physical devices.

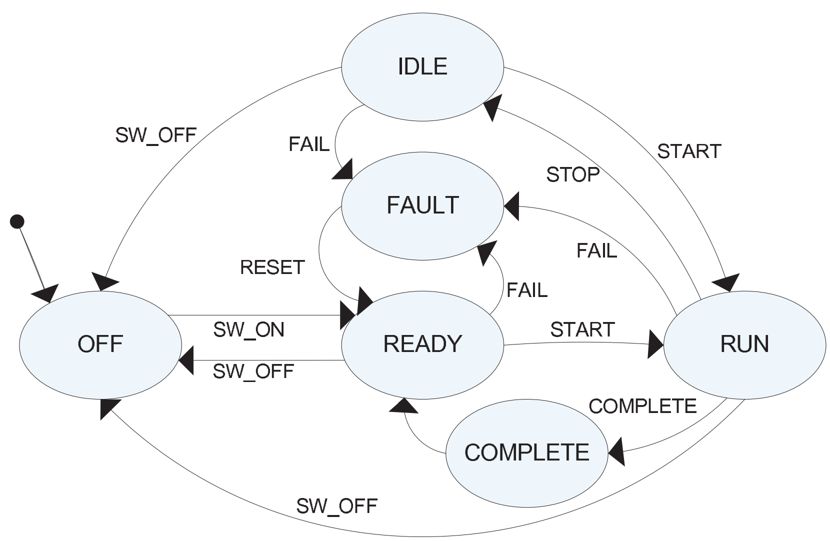


Figure 3.5 Appliance finite state machine.

More specifically, the appliance status may be:

- **Off**: appliance not enabled;
- **Ready**: enable asserted, appliance ready to start;
- **Run**: enable asserted and start command received, appliance consuming energy;

- **Idle**: enable asserted and stop command received, appliance not consuming energy;
- **Complete**: task completed and transit to "Ready" for being turned off or possible reinvoke;
- **Fault**: fault detected in the appliance.

The generic appliance interface is shown in Fig. 3.6, from where one can identify the input trigger signals: "Sych. Clock", "Start", and "Stop". The input "Time" will be used as an implicit signal in internal appliance management, as we will explain later. "Switch ON" and "Switch OFF" can be intended as enable signals, which correspond to the action of the user to manually switch ON/OFF the appliance. We assume that all the appliances that have been turned on are manageable.

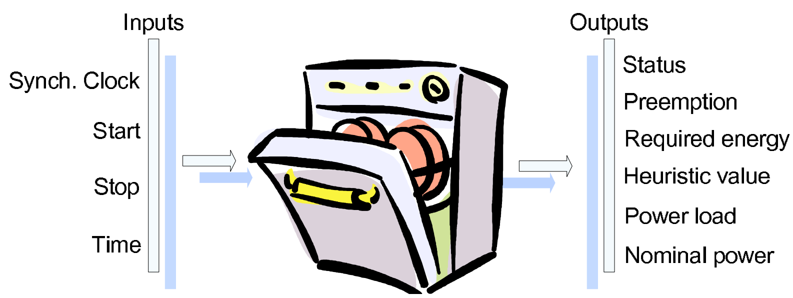


Figure 3.6 Appliance interface.

The outputs are: *Status*, *Preemption*, *Required energy*, *Heuristic value*, *Power Load* and *Nominal Power*.

Preemption indicates whether the task can be interrupted or not by the AC in order to give priority to a more urgent task. For example, regular loads will set the task preemption state to *true* when the temperature is within the desired range (appliance comfort zone), otherwise the associated task is non preemptive. For tasks with a fixed deadline, as for example burst loads, preemption state is set to *true* if there is still enough time left to complete the task before the deadline. If the task is delayed until its latest starting time or it has been frequently started and stopped within a short time period, the appliance intelligence turns the task to non preemptive.

Required energy is a value that indicates the total amount of energy needed by the appliance to either complete the assigned task (burst loads) or enter in the comfort zone (regular loads). Such value is used by the LB in order to schedule the task in a proper time period.

The *heuristic value* represents the urgency for the appliance to operate and, in our design, is a scaled value between 0 and 1. For example, appliances such as refrigerator or water heater have the heuristic value equal to 0 when the desired temperature is reached, otherwise an heuristic value equal to 1 when the internal temperature is at the boundary or outside the *comfort zone*. The upper and lower bounds of the comfort zone are, respectively, T_u and T_l. As an example, the refrigerator's comfort zone is defined in a way that the heuristic value h is computed as:

$$\begin{cases} h = 1 & T_{app} \geq UB \\ h = \frac{T_{app} - T_l}{T_u - T_l} & T_u < T_{app} < T_l \\ h = 0 & T_{app} \leq T_l \end{cases} \tag{3.1}$$

where T_{app} is the refrigerator internal temperature. For tasks with deadlines, the heuristic value is a function of the remaining time before the latest start time (LST), which is the latest useful moment in which the task should be started in order to be able to complete on time:

$$\begin{cases} h = 1 & t \geq LST \\ h = \frac{t - t_{arr}}{LST - t_{arr}} & t_{arr} < t < LST \\ h = 0 & t \leq t_{arr} \end{cases} \tag{3.2}$$

where t_{arr} is the request arrival time and t is the current time.

Evidently, there are open issues on how to compute the heuristic value, because for some users it may be more important to keep the rooms temperature within the desired range more than the water temperature in the boiler. Moreover, there is the question whether the heuristic value should be computed inside the appliances (decentralization of the intelligence) or inside the energy manager (centralization of intelligence). This project adopts the intelligence decentalization approach, in a way that the heuristic value is computed independentely inside each appliance.

Power Load is the value representing the instantaneous power consumed by the appliance, which may vary according to the state of the appliance. For instance if the appliance state is "Ready", the load will be much smaller than when it is in "Run" state. The nominal power consumed by the appliance during "Run" state should be assigned to the output variable "Nominal Power".

Each FSM can be easily adapted to represent a specific appliance and the generic interface allows for the development of a flexible DSM system, which can be easily extended with additional appliances and modules.

3.4 Admission Control

The basic concept of run-time scheduling is to control the operation of appliances in order to respect the limit on power capacity while satisfying criteria like, as for domestic applications, an adequate comfort level. Therefore, every appliance that sends a request is represented by a task, which is processed in a certain time window with respect to power load, preemption state, and priority characteristics. Note that if the available capacity is not sufficient, some tasks will be delayed. In order to meet acceptance criteria, the scheduler (AC and LB) might require the DRM to change the capacity limit, which in turn has to trade with the grid. Here is assumed that the available capacity is fixed between each AC invocation and an available capacity profile is defined for each LB invocation.

There exists a rich literature related to real-time computing systems scheduling (see, e.g., [Buttazzo (2005)]). Among the most used algorithms, one can find the Earliest Deadline First (EDF), Bratley or Least Slack Time (LST) scheduling algorithms. We found that the Spring kernel, developed in [Stankovic et Ramamrithan (1989)], is particularly suited for the problem considered in this work. More specifically, the Spring algorithm aims at finding a feasible schedule when tasks have different types of constraints, such as precedence relations, resource constraints, arbitrary arrivals, non-preemptive properties and importance levels. This is a NP-Hard problem, which solution may be too expensive to obtain in terms of computational effort, especially for dynamic systems.

As stated in [Buttazzo (2005)], in order to make the algorithm computationally tractable ($O(n^2)$ instead of $O(n \times n!)$) even in the worst case, the search in Spring algorithm is driven by a *heuristic function* H, which actively directs the scheduling to a plausible path. At each node of the search tree, function H is applied to each of the tasks that remain to be scheduled. The task with the smallest value determined by the heuristic function, called *heuristic value*, is selected to extend the current schedule. If a partial schedule is not feasible, the algorithm stops searching and returns the previous partial schedule (backtracking), which will be extended by the task with the second smallest heuristic value and so on. Note that, in order to reduce the computation time, the number of backtracking steps is limited as this algorithm is best-effort based instead of guarantee-based.

In order to adapt the Spring algorithm to our specific application, modifications have been introduced. More specifically, we consider the case where the priority of a task may change during the execution in accordance with all the appliance status. The priority is assigned basing on the heuristic value and, every time the AC is invoked, the execution pool for all the arrived requests may change. The main difference with the basic Spring algorithm is that the tasks are not scheduled until their completion, but just one time slice ahead. This is indeed an admission control policy, which makes the scheduler *myopic* but very flexible with respect to new task arrivals, task priority changes, and preemption state variations. The algorithm of the Admission Control is presented in Algorithm 1.

Algorithm 1 Admission Control

Variables:

- T: requests set
- j: request $\in$ T
- *P(j)*: nominal power consumption of the appliance associated to request j
- *utl*: accepted requests' cumulative power
- C: capacity limit

Require: Initialize the requests set (T) ordered by descending heuristic value

$utl = 0$
for all $j \in T$ **do**
  if $the\ task\ is\ running\ and\ non-preemptive$ **then**
    $accept\ request\ j$
    $remove\ request\ j\ from\ T$
    $utl = utl + P(j)$
  end if
end for
for all $j \in T$ **do**
  if $utl + P(j) <= C\ and\ request\ j\ is\ running$ **then**
    $accept\ request\ j$
    $remove\ request\ j\ from\ T$
    $utl = utl + P(j)$
  end if
end for
for all $j \in T$ **do**
  if $utl + P(j) <= C$ **then**
    $accept\ request\ j$
    $remove\ request\ j\ from\ T$
    $utl = utl + P(j)$
  end if
end for

3.5 Load Balancing

The Load Balancer spreads the electrical load over a time horizon in order to appropriately schedule the requests that have been refused by the Admission Control. The optimization is oriented toward minimizing the operations costs while maximizing the comfort level. Constraints are defined by the available capacity profile, tasks' deadlines and precedence constraints. One of the possible formulations of such a problem can be made with a mixed-integer programming model, which minimizes the total cost of energy consumption and is subject to constraints on tasks' characteristics and power consumption limitations.

Each task is scheduled over different time frames, which are adjacent for non-interruptible loads but not necessarily adjacent for interruptible loads. Note that the LB has a finite scheduling horizon and, in the presented formulation, it performs resource allocation for burst loads either non-interruptible or interruptible. Two basic assumptions for load balancing are:

- each appliance has a given power consumption load when it operates in the considered scheduling time horizon;
- information on energy price and power capacity limit is provided by DRM.

To present the formulation of load balancing, we consider a problem consisting of scheduling n appliances in a horizon containing m equal time frames. We denote by $\mathcal{N} = \{1, \ldots, n\}$ and $\mathcal{M} = \{1, \ldots, m\}$ two index sets corresponding to the set of appliances and the time frames respectively. Let $x_{ij}, i \in \mathcal{N}, j \in \mathcal{M}$, be a variable representing the activation state of the ith appliance in the jth time frame with value 0 or 1, representing the states "inactive" (OFF) and "active" (ON) respectively. Suppose that P_i is the power consumption and K_j is the energy cost per time unit. Then, $F_{ij} = P_i K_j$ defines a cost for appliance i to operate over the time frame j. Furthermore, for appliances requiring an operation over a continuous interval, we introduce binary variables, $d_{ij}, i \in \mathcal{N}, j \in \mathcal{M}$, equal to 1 if the appliance i is scheduled to start at the time frame j that force a contiguous allocation of time frames by using appropriate constraints described below. In general, we can also associate to each d_{ij} a startup cost denoted by G_{ij}. Hence, load balancing leads to a binary linear programming problem as follows (for non-preemptible loads scheduling):

$$\min \sum_{i,j} F_{ij}x_{ij} + \sum_{i,j} G_{ij}d_{ij}, \tag{3.3}$$

$$\text{s.t. :} \sum_{i} P_i x_{ij} \leq C_j, \ \ \forall j \in \mathcal{M}, \tag{3.4}$$

$$d_{ij} \leq x_{it}$$
$$t = j, j+1, \cdots j + \tau_i - 1, \ \ \forall j \in \mathcal{M}, \forall i \in \mathcal{N}, \tag{3.5}$$

$$\sum_{j} d_{ij} = 1, \ \ \forall i \in \mathcal{N}, \tag{3.6}$$

$$x_{ij} = 0, \ \ \forall i \in \mathcal{N}, \ \ \forall j \notin (T_i^{earliest}, T_i^{latest}), \tag{3.7}$$

$$d_{ij} \geq 0, \ \ \forall i \in \mathcal{N}, \ \ \forall j \in \mathcal{M}, \tag{3.8}$$

$$x_{ij} \in \{0, 1\}, \ \ \forall i \in \mathcal{N}, \ \ \forall j \in \mathcal{M}, \tag{3.9}$$

where C_j is the available capacity for the time frame j. The number of time frames to be allocated for appliance i, that requires a total amount of energy E_i, is defined by τ_i:

$$\tau_i = \left\lceil \frac{E_i}{P_i} \right\rceil$$

where $T_i^{earliest}$ and T_i^{latest} are, respectively, the earliest and latest start time of appliance i. Note that the set of constaints 3.5 do not apply to preemptible loads, which they can be scheduled in non-adjacent time frames. The four sets of constraints regarding this problem are specifically:

1. The total power consumption at each time frame has to respect the given capacity limit (Constraint (3.4)).

2. For each request a proper number of contiguous time frames is allocated so that each appliance is operated in a specific interval (Constraint (3.5)).

3. Each task is scheduled in an allowed operation period in such a way that each appliance is operated for a sufficient time in order to complete the working cycle before the deadline (Constraint (3.7)).

4. Each task is scheduled only once (Constraint (3.6)). This constraint can be relaxed accordingly to the task characteristics and requirements, in a way that if the task needs to be scheduled multiple times, more instances of the same task will be scheduled separately. Here activation dependencies can be managed through enabling coefficients.

The second set of constraints forces a total number τ_i of x_{ij} to one when a specific d_{ij} has been set to one. That is, when the optimizer decides the best time frame j for the appliance i to start, all $x_{i,j}$, $x_{i,j+1}$, ..., $x_{i,j+\tau_i-1}$ are forced to one. The third set of constraints sets to zero all those x_{ij} that correspond to the related appliances operation before the arrival time or after the deadline. Finally, the fourth set of constraints guarantees that each task is scheduled only once.

Note that the formulation presented above can be extended in order to take into account tasks' level of priority or dependent sequential requests by adding proper constraints.

3.6 Demand/Response Manager and Load Forecasting module

In this section we introduce the third layer of the DSM architecture, which includes the Demand/Response Manager and the Load Forecasting module. The DRM is concerned with energy price and consumption capacity bidding, while the LF is deputed to provide forecasts on dwelling consumption. As this research is not concerned with these modules implementation, we just present the functionalities and the interface they should have.

Demand/Response Manager (DRM)

This module trades with the Smart Grid the energy price and the consumption capacity by the means of the Demand/Response paradigm, and feeds such information to the LB and the AC in support of the load scheduling. This brings up the issue of QoS (Quality of Service), which is related to tenants comfort, an aspect whose assessment is behind the scope of this thesis.

If the AC or the LB reject requests, the requests rate of rejection (RR) raises accordingly. This latter information express, somehow, a discomfort of the tenants. If RR is high, the DRM requests the Smart Grid for more capacity in a way to maximize the user utility. Conversely, the Smart Grid may demand the users to lower their consumption by offering economic inducements. In such a case, the DRM will check the quality of service and the schedule filling rate in order to operate, where possible, adjustments on the capacity limit. It is clear how the practice of DSM raises up the issue of how to trade off QoS, peak shaving and savings.

Load Forecasting module (LF)

This module is deputed to provide forecasts of the dwelling consumption. Such a feature, based on the methods presented in Section 2.2.5, enable the DRM capability of trading energy for a long time horizon and enhance the LB optimality in scheduling loads ahead time.

3.7 Concluding remarks

This chapter presented an architecture for Autonomous Demand-Side management that, thanks to time-scale separation, has a layered structure. The Admission Control uses an on-line scheduling strategy and enables peak-load shaving in domestic power management. The Load Balancer, conversely, shows the benefits of performing optimal scheduling for operations in a longer time horizon, so as to reduce costs and meet the deadlines.

Such a control structure enables hierarchical control from higher levels, allowing to cope with more elaborate objectives related to energy management in Smart Buildings, including those achieving long-term optimal performances. Such a system also enables to trade energy in a Demand/Response paradigm, whether the DRM module is operative. LF module provides statistics on appliances usage and tenants habits, which will improve energy management. Although all the layers operate on different time scales, there could be issues if any expected information/decision at any level is delayed. In such a case, the interested module should appeal to sub-optimal decision strategies, which would balance user discomfort with consumption constraints.

The proposed architecture is scalable and integrable with other control policies since allows to change the algorithms and the models used within each module without any loss of functionality. It is flexible and enables the implementation of autonomous demand side energy management for a large variety of consumers, ranging from homes to buildings, factories, commercial centers, campuses, military bases, and even micro-grids.

Although the implementation of this approach, presented in the next chapter, is not fully set-up and fine-tuned, we show how the energy management at customer side is performed by the means of Admission Control and Load Balancing, assess the performances of each technique and enlight the limitations.

CHAPTER 4

DSM IMPLEMENTATION AND CASE STUDY

4.1 Implementation in Matlab/Simulink

This section presents an implementation of the proposed architecture for DSM system with Matlab/Simulink®, together with simulation studies for a residential case study. The setup for simulations is presented in Fig. 4.1, which includes three regular loads (heating in two rooms and refrigerator) and three burst loads (washing machine, dishwasher, and dryer). The baseline load is modeled as a constant load of 20 power units during 20 time units.

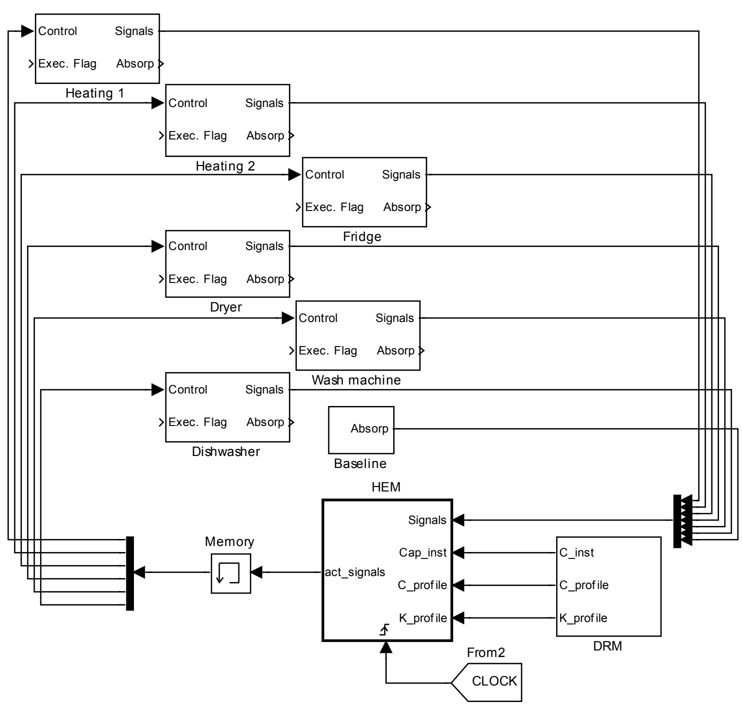


Figure 4.1 : DSM system implementation in Simulink.

The main components of the Home Energy Manager are shown in Fig. 4.2, which can be easily identified and cross-referred to the architecture proposed in Section 3.2. In simulation the time span is normalized to 100 time-units, which can be scaled depending on the application environment. The thermal dynamics of the appliances are set accordingly to represent a plausible behavior in such a time scale.

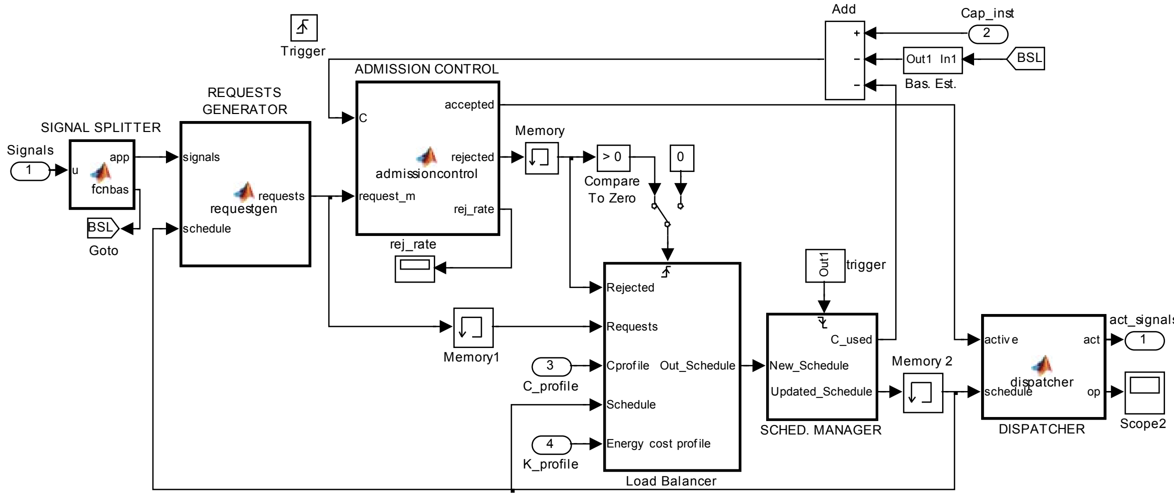


Figure 4.2 Home Energy Manager implementation in Simulink.

The following sections present the details of each component of the DSM system.

4.1.1 Smart Appliances

Smart appliances are implemented with the Simulink Stateflow Toolbox^{TM}and each appliance is able to compute internally the heuristic value and the energy required to complete the task. This latter information information allows the Load Balancer to compute the remaining time required to complete each task based on the power consumption. Heuristic values for regular loads are computed as linearly scaled factors between 0 and 1 inside the upper and lower bounds of the appliances comfort zones, while for the burst loads the heuristic values are linearly scaled depending on the remaining time to start. The appliance model is completed by coupling the state machine in Fig. 4.3 with the communication interface presented below.

Figure 4.4 shows the appliance embedded interface, which has been conceived regardless of appliance type. The block *app. interface* provides the appliance FSM with trigger signals depending on the control coming from the dispatcher (see Fig. 4.2). Note that *CLOCK* is a trigger signal for the appliances finite state machines and AC.

The room temperature, T_{room}, is obtained by combining the specific heat formulation (see eq. (4.1)) with the Fourier's law in its integral formulation for homogeneous material in 1-D geometry (see eq. (4.2)) [Holman (1997)], and integrated in time as:

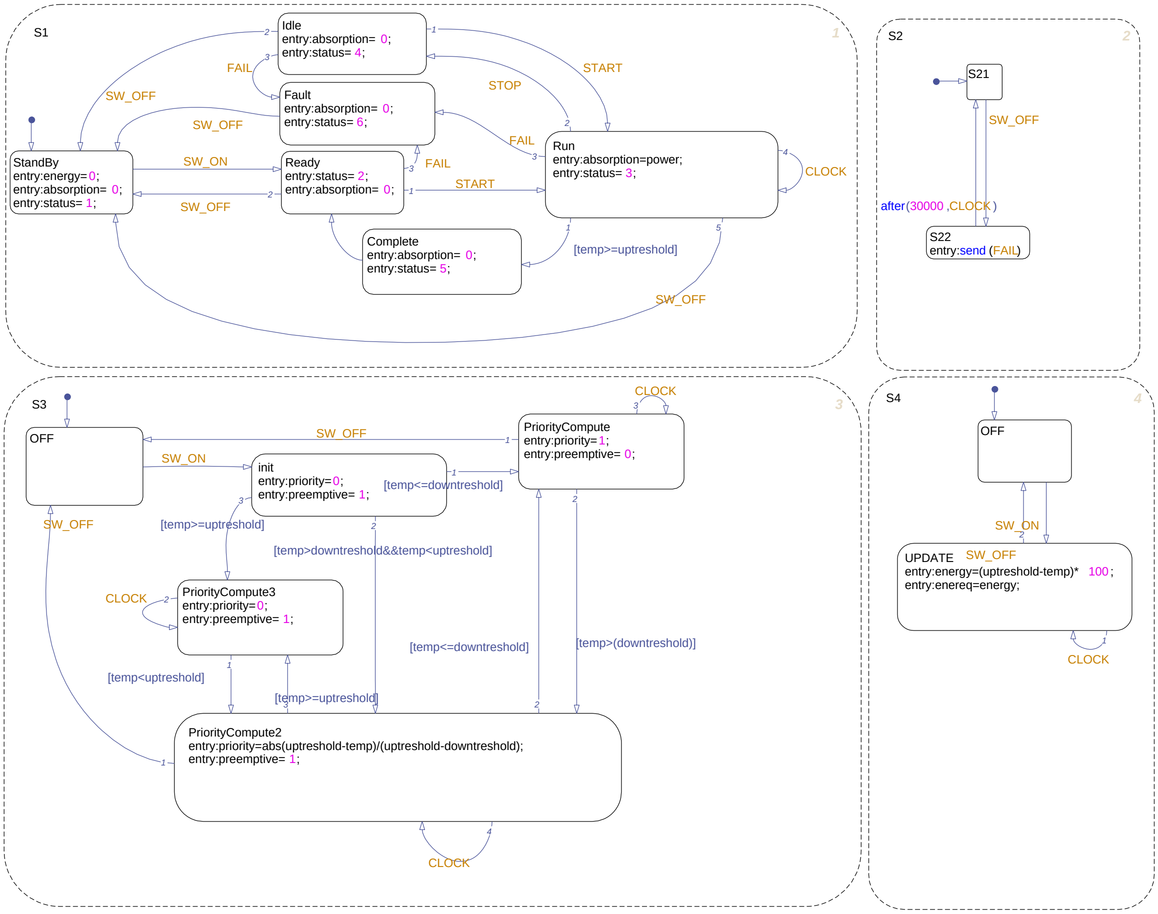


Figure 4.3 Smart Appliance implementation with the Stateflow Toolbox (heating)

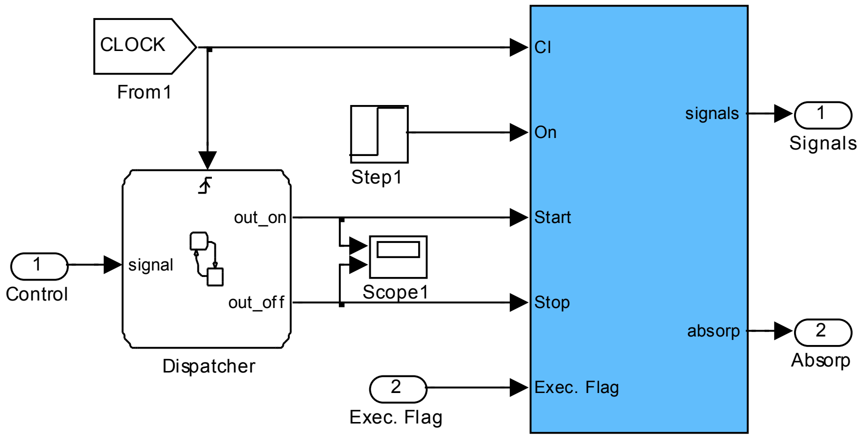


Figure 4.4 Smart Appliance interface

$$\frac{dQ_{tot}}{dT_{room}} = mC, \tag{4.1}$$
$$\frac{dQ_{exch}}{dt} = -KA\Delta_T, \tag{4.2}$$

where:

$$\Delta_T = T_{ext} - T_{room},$$
$$Q_{tot} = Q_{exch} + \eta_h P_h.$$

T_{ext} is the external temperature, P_h is the heater power, η_h is the heating system thermal efficiency, K is the room global thermal conductivity, and C and m are air specific heat capacity and mass, respectively. The evaluation of the temperature in the refrigerator is simulated using the same formula with adjusted parameters.

Finally, the block *Request Generator* is used to poll the signals coming from smart appliances and to create requests for the Admission Control. Basically, in this implementation such a block is not only a requests generator/aggregator but also is a part of the interface for smart appliances. Note that this module does not generate requests for those appliances whose operation has been already scheduled by the Load Balancer.

4.1.2 Admission Control

The AC is triggered every 10^{-2} time-units (period of the *CLOCK* signal), while the other layers are event-triggered. When the AC rejects a request coming from a burst load, the LB is activated in order to place the request in the existing schedule. In fact, a limit of the proposed implementation is that the LB does not reschedule all the requests at each triggering, instead it places new arrived requests where it is possible according to the available capacity and deadlines. Admission Control is fed at each invocation with requests coming from the Requests Generator and available capacity such that it allows to start a set of appliances in respecting the capacity limit. The requests are sorted by descending order of heuristic value before they are fed to the Admission Control. Note that non-preemptive tasks will not be stopped until they are completed. Conversely, each time the AC is invoked, preemptive tasks might be interrupted in favor of tasks with higher priority. Each time the AC is invoked, the execution pool may change according to new arrived tasks. Therefore, this algorithm is efficient in terms of peak-load shaving but it may not be optimal with respect to long-term performances, as we will show in simulation. An example of scheduling operation is shown in Fig. 4.5.

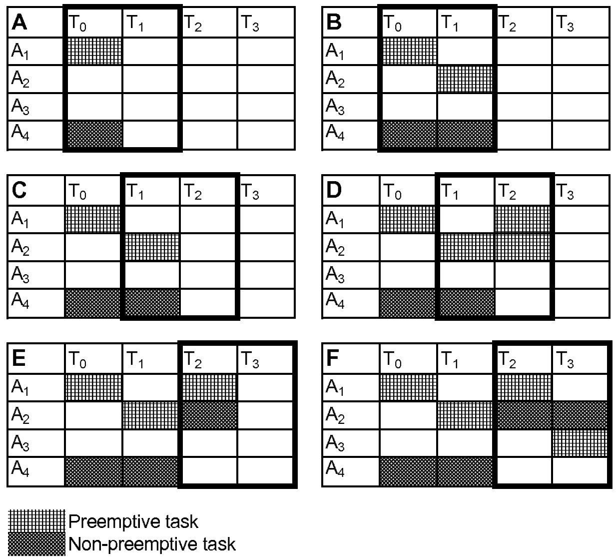


Figure 4.5 Example of scheduling operation

The operations are presented below:

1. The AC is invoked between time frames T0 and T1, while the appliances A1 and A4 have been running in the time frame T0 (Table A). Let assume that the line capacity is able to support two appliances simultaneously, all the loads are regular loads and at this moment the priority order is: A2 $\rightarrow$ A1 $\rightarrow$ A4 (A3 not yet arrived). A4 is non-preemptive and it is not completed, in a way that A1 has to share the remaining capacity with A2 (which has higher priority than A1). In this way A1 will is stopped in favor of A2. The execution pool for time frame T1 is then compiled and dispatched (Table B).

2. Once T1 has elapsed, the AC is invoked again. Assuming that in T1 task A4 was completed (table C), task A1 is free to start again. Now the priority order is: A2 $\rightarrow$ A1 and no other requests arrived. The execution pool for T2 is compiled and dispatched (Table D).

3. During the execution in time slice T2, task A2 became non-preemptive (due to its internal status). Meanwhile, task A3 arrived with higher priority than A1 (Table E). This situation pushes the scheduler to continue the execution of A2 (non-preemptive and not yet completed) and stop A1 in favor of A3. The execution pool for time slice T3 is then compiled and dispatched (Table F).

4.1.3 Load Balancing

The Load Balancer is implemented as an embedded Matlab function and the optimization routine is invoked in simulation as Matlab extrinsic function. At each invocation of the LB an optimization problem, as it has been defined in Section 3.5, is formulated and the binary integer programming framework is used to solve it with an algorithm of branch-and-bound. The node search strategy is the *depth-first search*, which chooses a child node one level down in the tree if that node has not already been explored. Otherwise, the algorithm moves to the node one level up in the tree and continues the search [The Mathworks Inc. (2011)].

Every time the LB is triggered, the simulation pauses and the optimization routine is invoked. In order to limit the iterations, the optimization time is constrained to 60 seconds. During this period the algorithm will return the best schedule among all the feasible solutions, otherwise the pending requests are rejected to the respective appliances, which will have to appeal again the AC for operation allowance.

4.1.4 Schedule Manager and Dispatcher

The dispatcher is a module that is activated each AC invocation and it is deputed to send control signals to appliances in accordance with the schedule provided by the LB and the AC. The dispatcher is implemented as Matlab embedded function in system in Fig. 4.2, and its code is presented in the Annexes section.

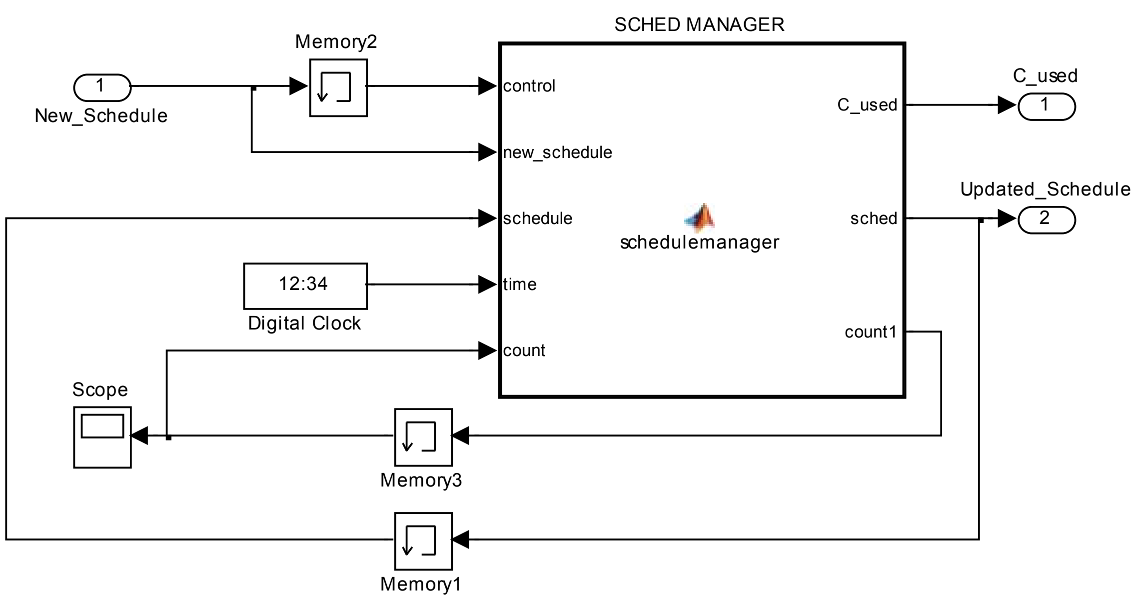


Figure 4.6 Schedule manager

The schedule is divided in ten time windows of ten time units each. As the simulation runs, the execution pool of burst loads during the current time window cannot be modified by the LB. In this context, the schedule manager provides the execution pool at each time window to the dispatcher. Once a time window has elapsed, it is eliminated from the schedule and a void window is added at the end of the schedule. For details about the schedule manager code, please refer to the Annexes.

4.2 Case Study

In this section we present simulation results to show the advantage of using admission control for load shaving and highlight the improvements of long term optimization using load balancing. The initial conditions are the same for the first three simulation cases: all the requests arrive at the same time and burst loads deadlines are 40, 40 and 70 time units. Each appliance has a power consumption of 20 power units and the external temperature is constant and equal to 20°C. The comfort zone for rooms 1,2 is 22°C-24°C and for the refrigerator is 2°C-5°C. The internal temperatures are initialized at 22°C, 20°C and 15°C for rooms 1,2 and refrigerator respectively. The last simulation study will show AC and LB limitations in case of insufficient capacity.

4.2.1 Power consumption without load management

This simulation considers the case study in which no control is performed on electric consumption. All the temperatures, in rooms and refrigerator, are initialized outside the comfort zone and the burst loads are initialized at the beginning of simulation. In this way, the devices are free to operate according to their internal status, which leads to a peak consumption of 120 power units. Total consumption, appliances operation, temperatures and baseline load are shown in Fig. 4.7

4.2.2 Peak load shaving via Admission Control

The second case study is designed for verifying the performance of energy management using exclusively online scheduling strategy (Admission Control). The capacity limit is set to 40 units, which is 1/3 of the possible maximum power consumption. Figure 4.8(a) shows that load peaks have been reduced such that the constraint on capacity is respected. However it can be seen from Fig. 4.8(c) that the deadline regarding the last burst load is violated. Such situation is caused by the sub-optimality of the online scheduling strategy used within the Admission Controller. The temperature evolution of appliances is depicted in Fig. 4.8(d), which shows a deviation from the comfort zone when the burst loads are operated. The aforementioned deviation is clearly caused by the capacity limitation and is the price to pay

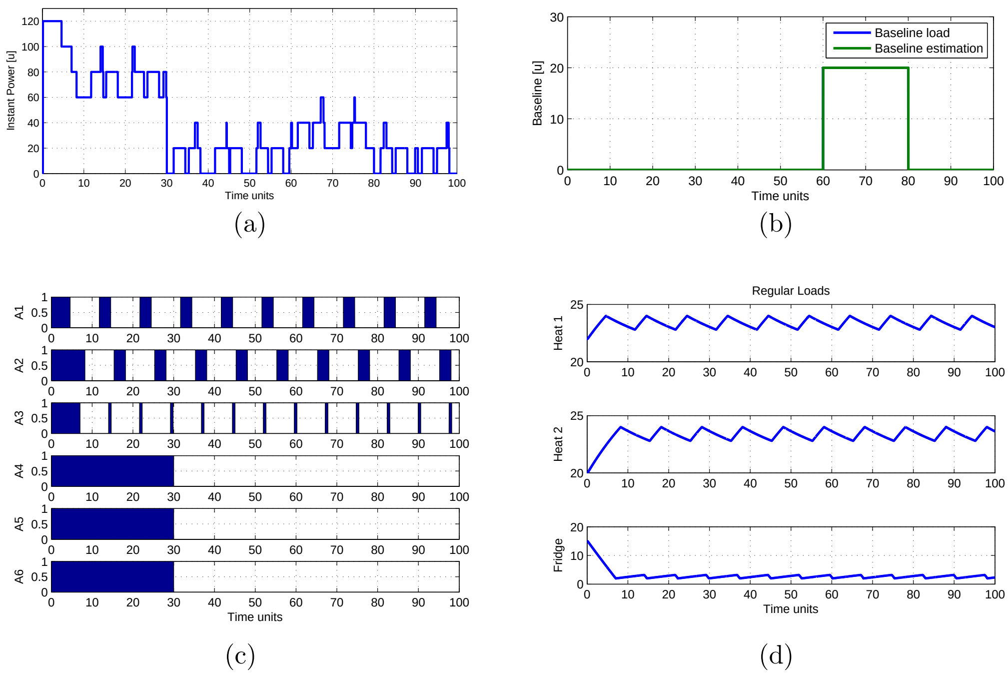


Figure 4.7 Case without load management: (a) total consumption; (b) baseline load; (c) appliances operation; (d) temperatures evolution.

for shaving load peaks. An increase of the available capacity allows more appliances to run in parallel, in a way that burst loads are operated respecting the deadlines and regular loads status deviate less from the comfort zone (see, e.g., Fig. 4.9).

4.2.3 Peak load shaving via Admission Control and Load Balancing

The third case shows that the use of Load Balancing enables the burst loads while respecting constraints on deadlines and capacity. Fig. 4.10(a) confirms that the constraint on capacity is respected and Fig. 4.10(c) shows that deadlines on burst loads are met. Here the load balancing produced an optimal schedule.

One can observe from Fig. 4.10(d) that temperatures related to regular loads still deviate from the comfort zone. However, such deviation is advanced in time with respect to the previous simulation since burst loads have been scheduled in advance by the LB and operated so as to respect the deadlines, which is the major advantage brought by Load Balancing.

4.2.4 Failure due to excessive request

The last simulation presents a case study where the energy management system fails to respect the constraint on capacity limit. In this setup the refrigerator internal temperature is

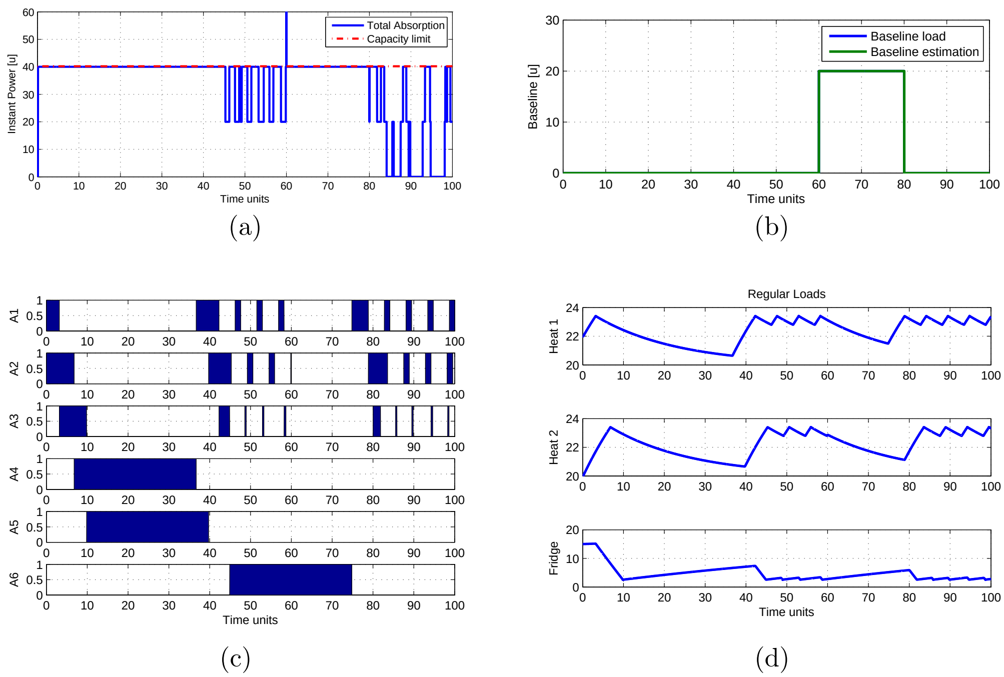


Figure 4.8 Peak load shaving via online scheduling: (a) total consumption; (b) baseline load; (c) appliances operation; (d) temperatures evolution.

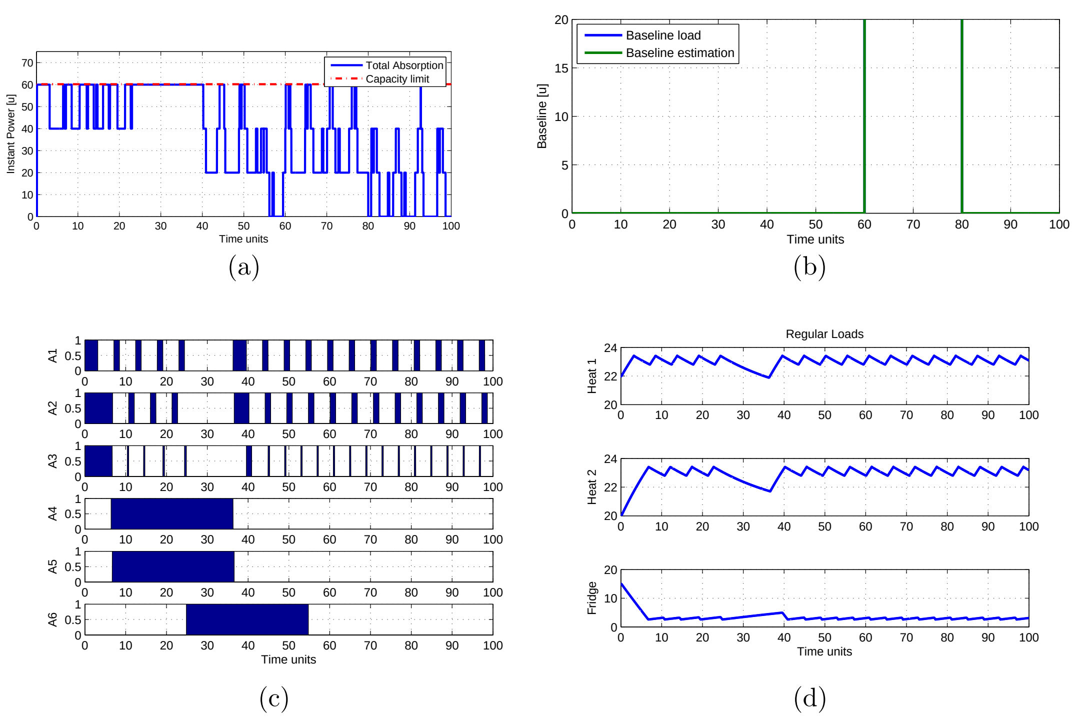
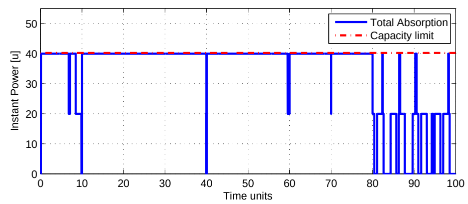
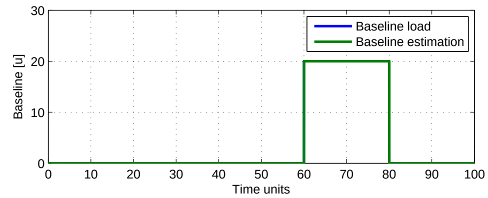


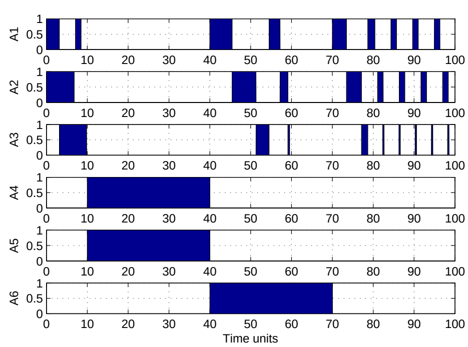
Figure 4.9 Peak load shaving via online scheduling (increased capacity): (a) total consumption; (b) baseline load; (c) appliances operation; (d) temperatures evolution.



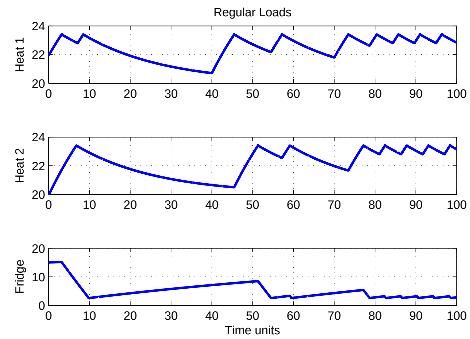
(a)



(b)



(c)



(d)

Figure 4.10 Peak load shaving via online scheduling and load balancing: (a) total consumption; (b) baseline load; (c) appliances operation; (d) temperatures evolution.

initialized at 25°C. Total power consumption, activation states, and temperatures evolution are shown in Fig. 4.11(a), Fig. 4.11(c), and Fig. 4.11(d) respectively. In this case, when the burst loads are forced to operate by the LB, the refrigerator preemption status is still *false* because of the internal temperature, in a way that the total consumption overpasses the capacity limit by 20 power units. Such a situation occurs because the LF module is not available. In case that accurate forecasts on regular loads and baseline would have been available, LB would have notified the DRM in advance about such failure, in a way that appropriate actions would have been taken. As soon as the refrigerator is preemptible again, it is stopped in order to reduce the home power consumption.

4.3 Conclusion

The case study presented in this chapter showed the benefits of using a DSM system for home appliances management with the aim of limiting load peaks. The online scheduling technique offers the means for regular loads activity synchronization in a way to respect capacity limits, while the LB offers optimal scheduling of burst loads with a view to minimizing energy consumption costs and respecting the deadlines.

Simulations can be more realistic thanks to refinement of the appliances models. The

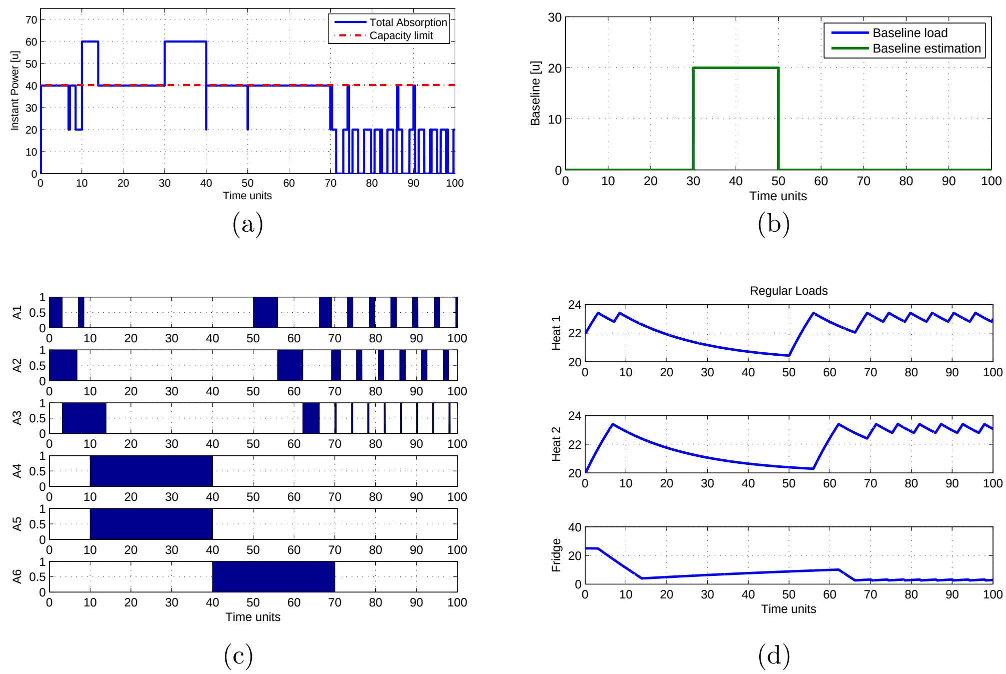


Figure 4.11 Failure due to excessive requests: (a) total consumption; (b) baseline load; (c) appliances operation; (d) temperatures evolution.

scheduling horizon may be extended in order to ease tasks placement when critical load situations occur, although the optimization complexity would increase accordingly.

The next chapter presents the experimental results of autonomous demand-side management via admission control, in the setup at RISØ DTU - National Laboratory for Sustainable Energy (DK).

CHAPTER 5

EXPERIMENTAL STUDY

5.1 Context

This chapter presents the design, implementation, and the first experimental results of the presented DSM systems for Smart Buildings in view of optimizing the energy demand in the Smart Grid. In this study the Admission Control, which is the bottom layer interacting in real-time with physical equipments, is addressed and the real-time power consumption management in a residential dwelling is implemented and tested in the FlexHouse at RISØ DTU. The experimental results provide a proof of concept for the proposed architecture and demonstrate the applicability of the developed approach in autonomous DSM systems for Smart Grids.

5.2 The experimental setup: FlexHouse at RISØ DTU

FlexHouse is a test facility organized as an office building that is a part of a SYSLAB research facility for intelligent, active and distributed systems at RISØ DTU National Laboratory of Sustainable Energy [RISØ-DTU (2011)]. FlexHouse is equipped as a modern office building, electrically heated with 10 space heaters and cooled by 4 conditioners. Tap water comes from a hot water storage tank and the space is illuminated by 24 fluorescent lamps. A small kitchen consists of a fridge and a coffee machine. Devices in FlexHouse are controlled remotely. The state of the building and appliances is read from various sensors. FlexHouse software infrastructure offers interfaces to all devices and easy access to the house's state as shown in Fig. 5.1.

Control actions are dispatched by the Home Energy Manager (an implementation of the proposed DSM architecture), which includes diverse function depending on appliances' intelligence. Since our aim is to prove a proof of concept for the architecture, the appliance interface inside this HEM represents only one of the possible implementations. FlexHouse layout diagram is shown in Fig. 5.2 and the air conditioning is available only in four rooms out of eight: room 1, room 2, room 3 and the main hall.

Electric heater is installed in all the rooms, while a refrigerator is placed in the main hall together with the control system, switch panels, and communication devices. The information system developed for SYSLAB and FlexHouse offers an easy access to actuators and sensors located in the building or embedded in the appliances. HEM developed in MATLAB can be

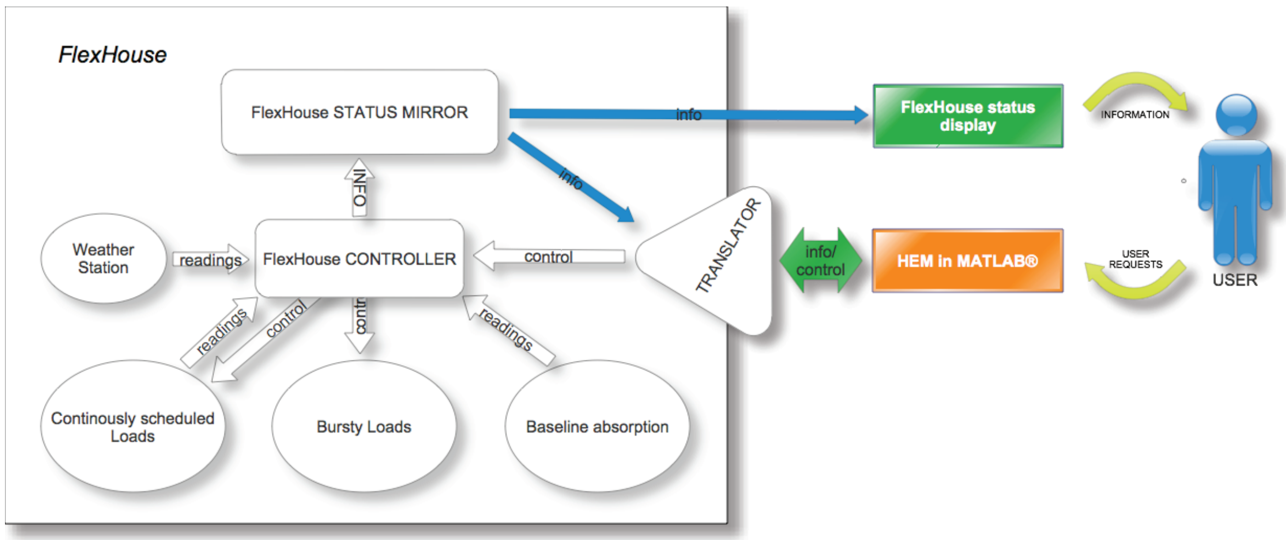


Figure 5.1 FlexHouse Control Scheme

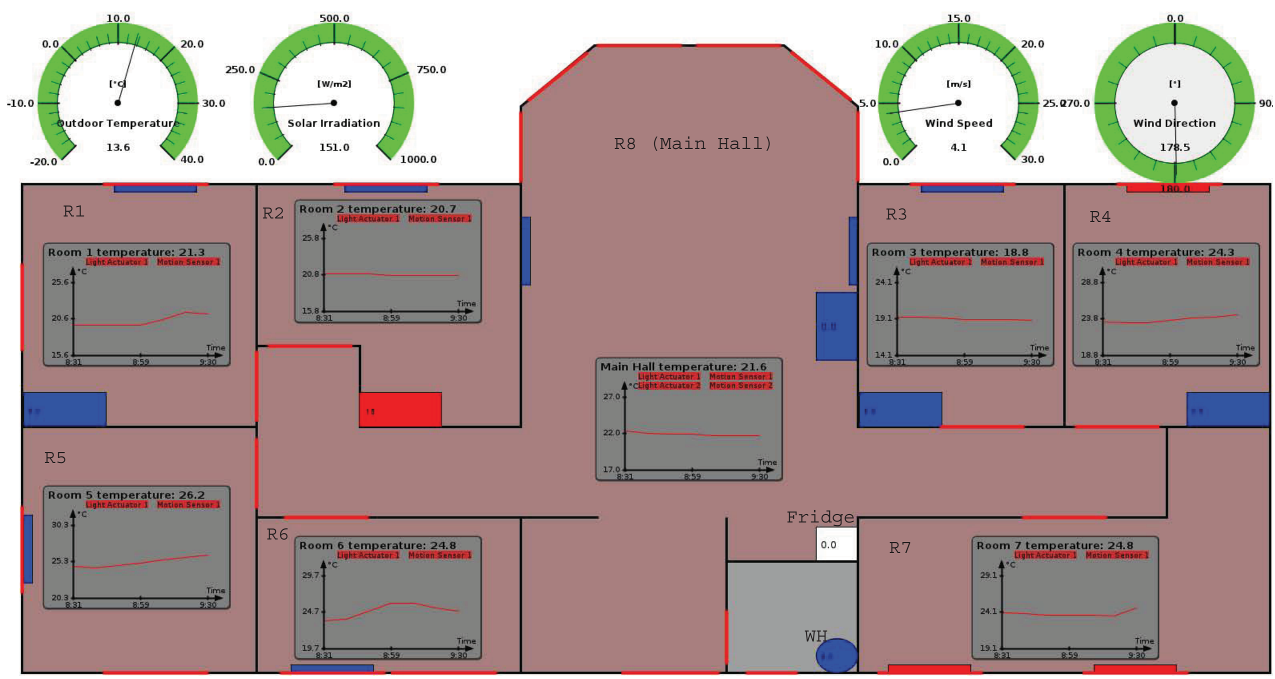


Figure 5.2 FlexHouse layout & state monitor

directly connected to a SYSLAB machine to exchange information with FlexHouse via Java Remote Method Invocation.

Each device in the FlexHouse is remotely controlled with sensors and actuators based on EnOcean® [Anders (2011)] communication standard that offers only one-way communication and cannot handle acknowledgement exchange. However, the FlexHouse controller is equipped with a software state mirror that tracks the state of the house by taking into account all the control signals exchanged between the controller and the devices (see Fig. 5.1). Thanks to this feature, the HEM can retrieve appliances' status when needed.

Heaters, lights, and boiler are controlled by EnOcean switches, while the refrigerator is connected to an EnOcean-based smart plug. The AC, heaters, boiler, and refrigerator have internal thermostats set to the highest and lowest setpoint respectively, in a way that the HEM can actively operate the temperature control based on the comfort zones.

Weather information, such as wind direction and speed, solar irradiation, and outside temperature, is provided by the weather station and the PV panels through dedicated interfaces.

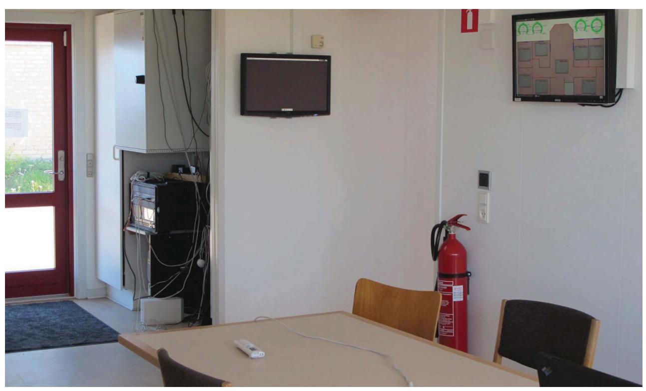


Figure 5.3 FlexHouse livingroom

Figure 5.4 FlexHouse and PV installation at RISØ DTU

Since heating and cooling capabilities are available only in five rooms, temperature control policies have to be designed accurately in order to ensure that heating and cooling systems will be triggered immediately when the temperature is very close to the required room temperature. To this end, we use an hysteresis logic with deadbands in order to manage air conditioning and heating when they are both available in the same room.

Information on total power consumption is needed when dealing with consumption constraints. The air conditioning consumption represents only a limitation, given that it cannot be estimated and modulated *a priori* because it depends on inside and outside heat exchange conditions (temperature, air flow, humidity, etc.). As the measured air conditioning consumption is between 250W and 600W, a conservative estimation of constant consumption of 500W is used in operation. The power consumption of heating modules is around 1000W and the refrigerator consumes 60W. Home automation infrastructure has an average consumption of 300W. Hence, the nominal total consumption of the house is about 11860W, excluding the baseline load.

5.3 Experimental Results

In this section, we present the experimental results and analyze the performances with respect to peak shaving and comfort management of such a DSM system.

5.3.1 Power consumption without load management

This experiment aims at demonstrating how the superposition of regular load causes high peak load. At the beginning, as the temperature of many appliances is outside the comfort zone, an important number of requests arrive at the same time. Since there is no limitation on power consumption, the AC will accept all the incoming requests. Temperature evolution and relative comfort zones in rooms from 1 to 8 (R1, R2,..., R8) are shown in Fig. 5.5(a) and Fig. 5.5(b). Total power consumption, outside temperature and refrigerator internal temperature are shown in Fig. 5.5(c). Fig. 5.5(a) and Fig. 5.5(b) show that tenants' comfort is respected in all rooms. Nevertheless, since air conditioning is not available in all rooms, external temperature and solar radiation can cause overheating in some rooms. Fig. 5.5(c) shows that if there is no control on the accepted requests, at the beginning the peak-consumption can be as high as 9940W while, after 20 hours of operation, at steady state the highest peak observed is 7200W.

5.3.2 Peak load shaving via Admission Control

In the experiment reported here, the Admission Control is operated with a constant capacity limit of 3000W. The DSM system schedules loads using the algorithm presented in Algorithm 1 in order to limit the consumption to the given capacity. We can observe from Fig. 5.6(a)

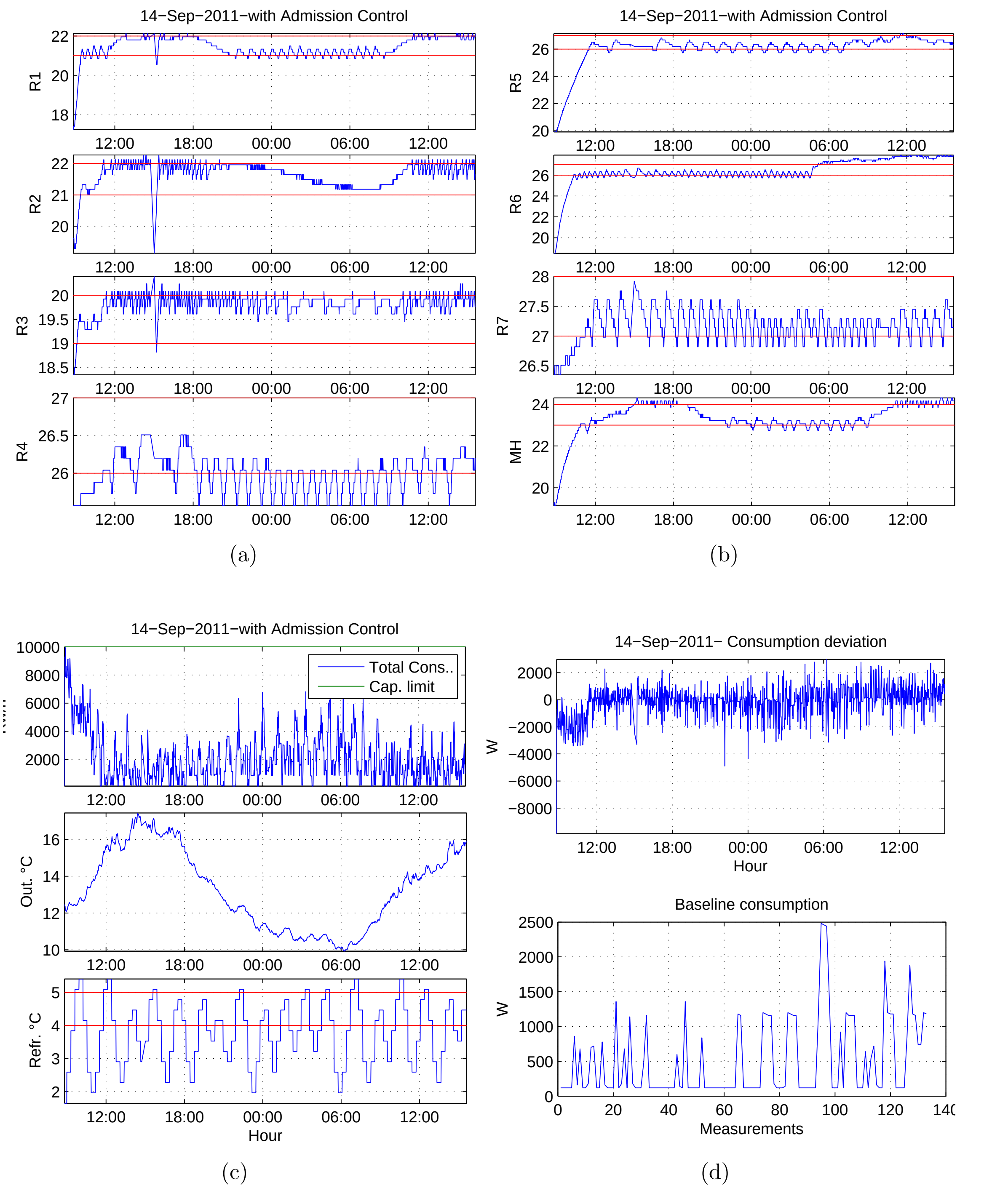


Figure 5.5 Case without load management: (a) Temperature in rooms from 1 to 4; (b) temperature in rooms from 5 to 8; (c) outside temperature and refrigerator internal temperature; (d) consumption deviation and baseline load.

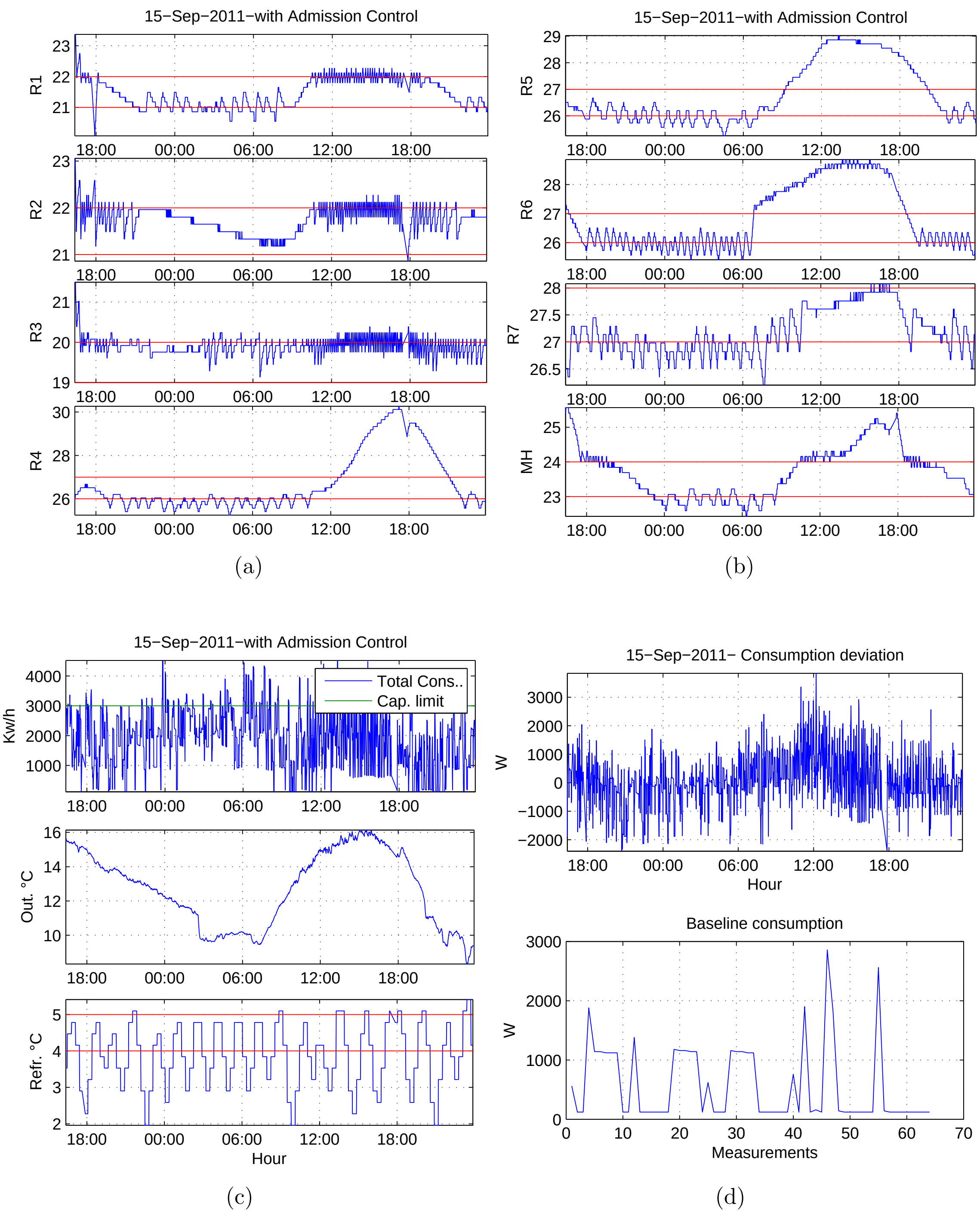


Figure 5.6 Peak load shaving via admission control: (a) Temperature in rooms from 1 to 4; (b) temperature in rooms from 5 to 8; (c) outside temperature and refrigerator internal temperature; (d) consumption deviation and baseline load.

and Fig. 5.6(b) that the temperature is kept in the comfort zone in all the rooms with AC and the overheating in the rooms without AC is natural during daytime. The refrigerator internal temperature is kept in the comfort zone as well, while the peak load is reduced (Fig. 5.6(c)) even if the capacity limit of 3000W is not always respected. In fact the highest peak is measured to be 4520W and it is caused by different factors, such as the uncertainty on a appliances' model (which is based on nominal power consumption) and baseline consumption variations. For instance the heaters and air conditioning consumption is not constant and there is no such a way to predict the baseline consumption, given the LF module is not yet implemented. Such disturbances have a negative impact on the performance of DSM with respect to the capacity limit compliance, as it is shown by the deviation from nominal consumption (first chart in Fig. 5.6(d)). The second chart in Fig. 5.6(d) shows the baseline consumption, which is sampled when all the appliances are turned off and contributes to the capacity limit violation. Given available historical data and tenants behavioral models, it will be possible to use them in the Load Forecast module to enhance load shaving performances.

Nevertheless, the DSM system shows its benefits in terms of the reduction of peak consumptions by 61.8% of the maximum nominal consumption (from 11860W to 4520W), by 54.5% in the experimental worst case consumption (at the beginning of the experiment, from 9940W to 4520), and by the 37.2% during steady state operation (from 7200W to 4520W).

5.3.3 Load management via Admission Control and baseline estimation

In order to work around the problem of appliances modeling inaccuracies and lack of LF module, in this paragraph we present an *ad hoc* solution for such specific experimental setup. In this context, the baseline load is supposed to incorporate the deviation of measured consumption from the expected consumption, which is made up by the summation of nominal power of running devices. Moreover, the baseline load is supposed to have enough slow dynamics, such that it may be approximated by the reading value between each pair of samples:

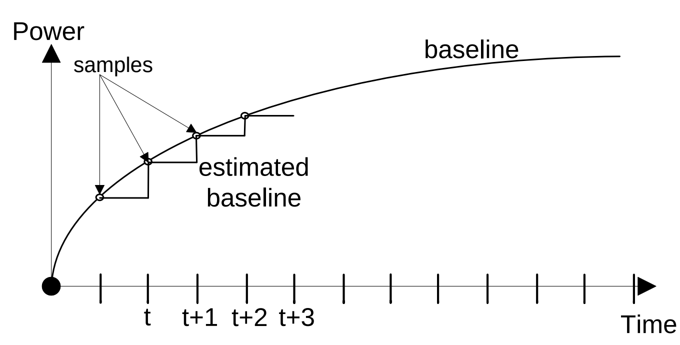


Figure 5.7 Baseline estimation

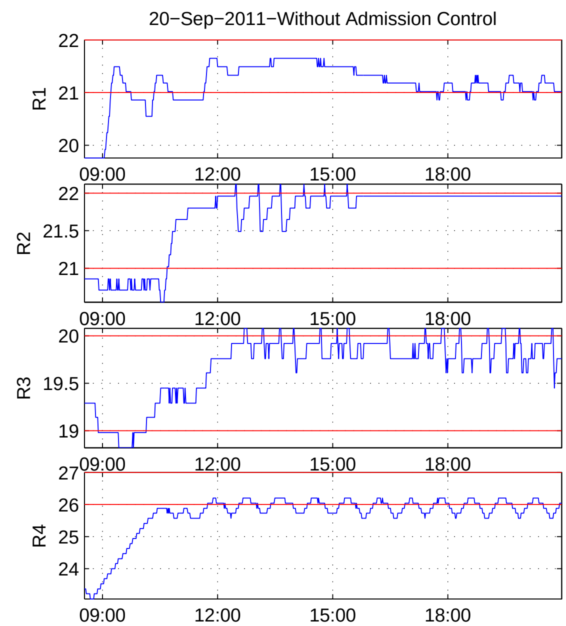
In order to compensate the effects of appliances modeling inaccuracies and unavailability of accurate measurements of baseline load, at each invocation the Admission Control subtracts from the available capacity the consumption deviation. This latter value is computed as the difference between the measured total consumption and the sum of each active appliance nominal power (expected consumption):

$$\begin{aligned}
&C_{av}(t) = C_{lim}(t) - \hat{B}(t) \\
&\hat{B}(t) = A_m - \sum_j P_j x_j \\
&x_j \in [0,1] \ , \ j \in \mathcal{N}
\end{aligned} \tag{5.1}$$

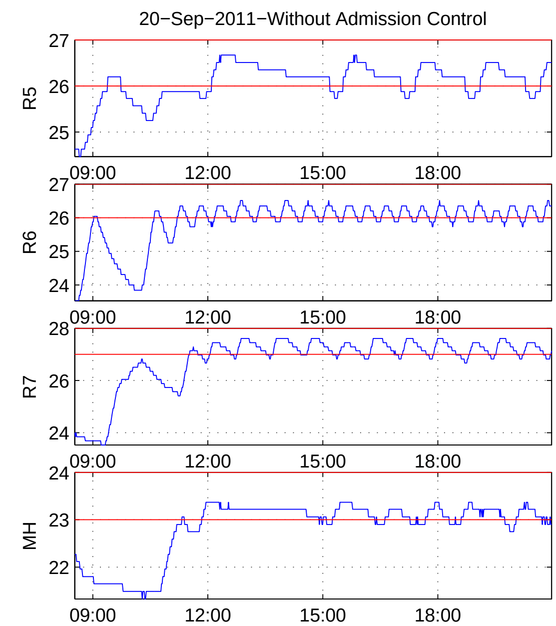
where C_{av} is the available capacity, C_{lim} is the capacity limit, $\hat{B}$ is the estimated baseline load, A_m is the FlexHouse total electric absorption (provided by a central power meter), P_j is the nominal power consumption of appliance j and x_j is its activation status. Fig. 5.8 shows the effectiveness of the proposed solution with respect capacity limit compliance.

5.4 Conclusions

As shown in Section 5.3.3, the effectiveness of peak load shaving is sensitive to appliances modeling and feedback information, issue that stays open in this research. Indeed, when passing from simulation to implementation, improve appliances' models, define tenants' comfort metrics, set up adaptive auto-tuning models for the *house system* are essential achievements. Those latter futures development is highly interesting given that, concerning temperature management, appliances influence each others during their operation.



(a)



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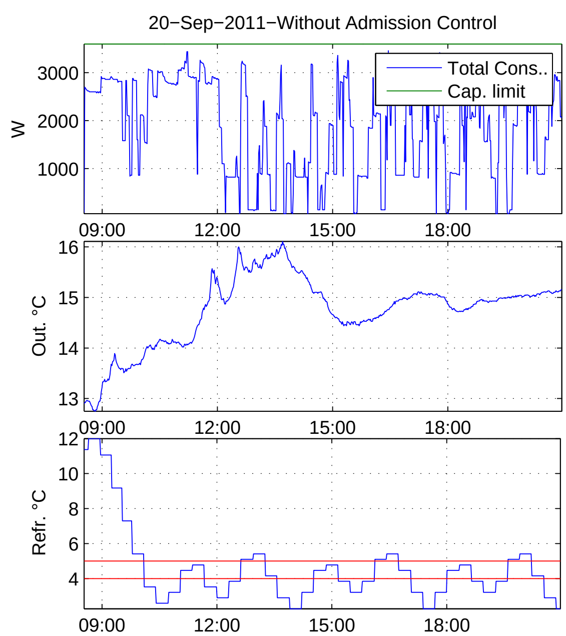

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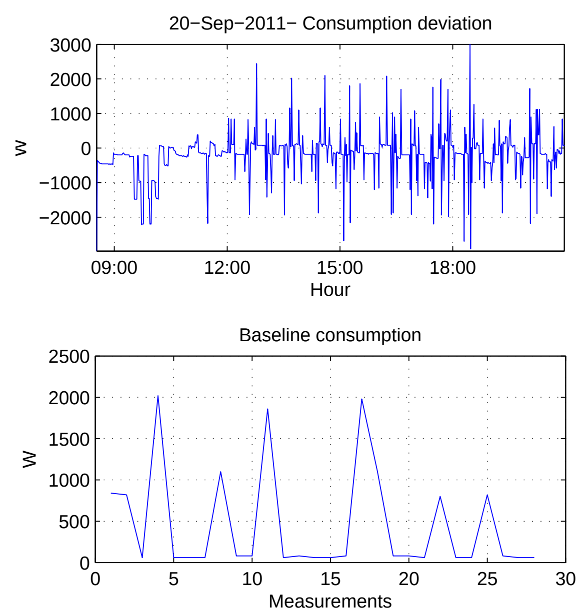

(d)

Figure 5.8 Peak load shaving via admission control and baseline estimation: (a) Temperature in rooms from 1 to 4; (b) temperature in rooms from 5 to 8; (c) outside temperature and refrigerator internal temperature; (d) consumption deviation and baseline load.

CHAPTER 6

CONCLUSIONS AND FUTURE WORK

This research strives at putting forward an original point of view of demand side load management, proposing a framework for autonomous energy management at customer-side in the Smart Grid. This framework is suitable for a dynamic environment such as the Demand/Response, and can be used at different levels of the Smart Grid. Even though the implementation proposed in this thesis is in the early stages of development, consistent simulation and experimental results of peak load shaving provided a proof of concept. The chapter dedicated to the literary review gives an idea of how new the technology of Smart Grids is, and how fervent the research in this domain is. For instance, the present investigation addresses and proposes solutions for some aspects of DSM, but does not solve other issues, such as energy pricing, large-scale optimization, load forecasting, communication technologies, and Smart Buildings integration within Micro Grids.

For example, an interesting study in [Mardavij Roozbehani (2010),Mardavij Roozbehani et al. (2011)] presents a new model for electricity real-time retail pricing whereby a feedback Demand/Response paradigm is proposed and its stability and efficiency are assessed. Concerning the demand-side load management, another interesting point of view is presented in [Amir-Hamed Mohsenian-Rad et Leon-Garcia (2010)] where a distributed D/R paradigm is assessed based on a game-theoretic approach. In such distributed architecture, the information exchange between customers and utilities tends to explode as the number of users increases. This is a typical situation in self-organizing systems, where the independence of each entity has to be traded for the reliability and amount of communication. On the other hand, centralized control architectures can achieve a higher optimality, at the price of a higher risk of failure in case of communication collapse between the leader and the clients.

The DSM system proposed here has been conceived with a layered architecture based on the decentralized/hierarchical control paradigm, where each layer operates independently and at maximum of its *potential*. This allows to reduce drammatically the communication between layers, which occurs in the case of insufficient information or infeasible solutions, information exchange between users and information exchange between users and utilities.

Smart Buildings integration with Micro Grids and renewable energy sources is among the most interesting applications of such a DSM system, a topic that is assessed in [Xiaohong Guan et Jia (2010)]. In this latter study a mixed-integer optimization approach is used to coordinate all the loads and energy sources in the Micro Grid. An issue rising up from such a complex model is the computational feasibility with respect to time constraints. This latter argument addresses future research on optimization problems and sub-optimal strategies applied to real-time energy market and load scheduling.

Even if the demand-side management is only one feature, it is an enabling technology for many components of the Smart Grid. Efficient DSM will enable a high penetration of renewable energy sources such as solar and wind power, and the integration of Smart Buildings with local generation in the micro grids. It will give the means for effective electricity dynamic pricing and liberalization of energy markets, where the customers will be encouraged to consume less and be more efficient so as to minimize their energy expenses. Such practices have immediate benefits for the environment, thus allowing for its protection, making it economically viable.

From these latter considerations, one can think about another realm of possible developments in terms of energy trading. In fact, as energy demand is constantly increasing, various energy trading companies have been recently established. Such business is very attractive for utilities, traders, and customers, and is based on customer aggregation. There exist companies that offer load shedding services to the grid by contracting consumption decrease with their customers. In such a context, customers are asked by the aggregator to modify their consumption for a given time period, in exchange of an economical incentive. In this way, the aggregator can offer ancillary services to utilities by offering load shadding, service that has a consistent economic value depending on the moment it is offered. At the current state of the art, such kind of DSM is operated via *manual* customer notification. However, in the near future, this system may be enabled to aperate automatically. As a natural evolution of this latter practice, one can think about commercial customers, for instance whose shedding capacity may be considerable in the case of shopping malls. With this vision, it is not difficult to imagine that typical practices of stock markets may be applied to the energy market. Evidently, the aformentioned topic raises up ethical and social issues, whose investigation will hopefully be exhaustively carried out.

In conclusion, I hope this research constitutes a starting point for future developments in the fields of engineering, mathematics, social sciences, and economics, in the light of putting Science at the service of Humanity and environment preservation.

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ANNEX A

MATLAB CODE OF ADMISSION CONTROL BLOCK

```
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%
% The usage of any part of this code for commercial pouposes should be
% authorized by the author. Any part of this code can be used for academic
% purposes upon citation.
%##########################################################################
% request(1)= appliance id {1..N}
% request(2)= appliance status {1,2,3,4,5,6}, (1=off, 2=ready, 3=run,
%                                              4=idle, 5=complete, 6=fault)
% request(3)= preemption {0,1}
% request(4)= required energy (1..E)
% request(5)= heuristic value (0,1)
% request(6)= power load {0,P}
% request(7)= execution flag {0,1}
% request(8)= arrival time {t}
% request(9)= deadline {t,t+m}

function [accepted,rejected,rej_rate]=admissioncontrol(C,request_m)

% NB: when you want to deactivate the AC you need to change three
% things in the program: treshold, commented parts in the last loop of AC,
% and rise up the capacity in the initialization script sim_init.m

request_matrix=sort_heuristic(request_m);
rjr=0;
m=size(request_matrix,1);
%treshold=0; environment=0;% to use when we don't want the AC active...
treshold=0.3; environment=1;
tot=0;

%##########################################################################
% here we create the support vector for the acctivations
act=zeros(1,m);

%##########################################################################
% here we accept those requests that belongs to tasks that are
% non-preemptive and were operating at the previous time frame.
for k=1:m
    if (request_matrix(k,1)~=0 && request_matrix(k,2)==3 && request_matrix
        (k,3)==0 && request_matrix(k,4)>0.1)
        act(request_matrix(k,1))=1;
```

```
        tot=tot+request_matrix(k,6);
        request_matrix(k,:)=0;
    end
end

%########################################################################
% here we accept those requests that respect the schedulability condition
% and have been running at the previous time frame or have maximum
% heuristic value
for k=1:m
    if (request_matrix(k,1)~=0 && tot+request_matrix(k,6)<=C &&
        treshold<request_matrix(k,5) && request_matrix(k,2)==3 &&
        request_matrix(k,4)>0.1)
        act(request_matrix(k,1))=1; % activation flag
        tot=tot+request_matrix(k,6);
        request_matrix(k,:)=0;
    end
end

%########################################################################
% here we fill the remaining capacity with the remaining requests

if environment
    for k=1:m
        if (request_matrix(k,1)~=0 && tot+request_matrix(k,6)<=C &&
            0.6<request_matrix(k,5) && request_matrix(k,4)>0.1)
            act(request_matrix(k,1))=1; % activation flag
            tot=tot+request_matrix(k,6);
            request_matrix(k,:)=0;
        end
    end
else
    for k=1:m
        if ((request_matrix(k,1)==4||request_matrix(k,1)==5||
            request_matrix(k,1)==6) && tot+request_matrix(k,6)<=C &&
            0<request_matrix(k,5) && request_matrix(k,4)>0.1)
            act(request_matrix(k,1))=1; % activation flag
            tot=tot+request_matrix(k,6);
            request_matrix(k,:)=0;
        else
            if (request_matrix(k,1)~=0 && tot+request_matrix(k,6)<=C &&
                0.6<request_matrix(k,5) && request_matrix(k,4)>0.1)
                act(request_matrix(k,1))=1; % activation flag
                tot=tot+request_matrix(k,6);
                request_matrix(k,:)=0;
            end
        end
    end
end
accepted=act;
rej=not(act);
for i=1:m
    if request_m(i,4)<1 %if the required energy is small, the task should
        %not belong to the rejected tasks
```

```
        rej(i)=0;
    end
end
rej_rate=sum(rej);
rej(1:3)=0;
rejected=rej;
end

% ########## FUNCTION SORT HEURISTIC ##########
function list=sort_heuristic(requests)
b=size(requests,1);
temp=[(1:b)' zeros(b,1)];
req=zeros(size(requests));
for j=1:b
    temp(j,2)=requests(j,5);
end
[B,I]=sort(temp,1,'descend');
temp=[I(:,2) B(:,2)];
for j=1:b
    req(j,:)=requests(temp(j,1),:);
end
list=req;
end
```

ANNEX B

MATLAB CODE OF LOAD BALANCER BLOCK

```
%###########################################################################
% Copyright:    Giuseppe Tommaso Costanzo
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%
% The usage of any part of this code for commercial pouposes should be
% authorized by the author. Any part of this code can be used for academic
% purposes upon citation.
%###########################################################################
function output_sched=loadbalancer(rejected,request_matrix,schedule,C,K)
m=size(schedule,1);
coder.extrinsic('loadbalancerSIMULINK','datestr','now','displayrequests')
displayrequests(request_matrix)
rejected
tobalance=request_matrix(rejected,:)
a=datestr(now)
SCHED=schedule;
SCHED=loadbalancerSIMULINK(tobalance,schedule,C',K');
output_sched=[(1:m)' SCHED(:,2:end)]
end
```

ANNEX C

MATLAB CODE OF LOAD BALANCER BALGORITHM

```
%##########################################################################
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%
% The usage of any part of this code for commercial pouposes should be
% authorized by the author. Any part of this code can be used for academic
% purposes upon citation.
%##########################################################################
% request(1)= appliance id {1..N}
% request(2)= appliance status {1,2,3,4,5,6}, (1=off, 2=ready, 3=run,
%                                              4=idle, 5=complete, 6=fault)
% request(3)= preemption {0,1}
% request(4)= required energy (1..E)
% request(5)= heuristic value (0,1)
% request(6)= power load {0,P}
% request(7)= execution flag {0,1}
% request(8)= arrival time {t}
% request(9)= deadline {t,t+m}

function output_sched=loadbalancerSIMULINK(request_matrix,schedule,C,K)

%request_matrix
m=size(request_matrix,1);
n=size(schedule,2)-1; % remember that the first column of the schedule is
                      % not a time frame, but contains the ids...
display(sprintf('Entering the Load Balancer... n=%u , m=%u',n,m));

%fictitious arrival times definition
display('LB: Arrival times')
a=request_matrix(:,8)'

% deadlines definition
display('LB: Deadlines')
d=floor(request_matrix(:,9)')/10

% tasks energy requests
display('LB: Energy requests')
e=request_matrix(:,4)'

% tasks power requests
display('LB: Power requests')
p=request_matrix(:,6)'

```

```
% available capacity profile
display(strcat('Capacity profile:',num2str(C)));
OPTIONS=optimset('Algorithm','sqp','NodeSearchStrategy','df','MaxTime',60,
'Display','iter');
utl=100*sum(e)/sum(C);
display(strcat('Utilization factor : ',num2str(utl),' %'))
if (utl>100)||(max(p)>max(C))
    display('The problem is unfeasible because of the capacity')
    output_sched=[];
else
    %######### Activation vectors
    act={};
    shift={};
    shift2={};
    tau=[];
    A0=[];
    A1=[];
    A2=[];
    b=[];
    b0=[];
    K1=[];
    Aeq=[];

    for j=1:m %appliances
        act{j}=zeros(1,n);
        act{j}(1,a(j):d(j))=1; % activation vector for task j
        Aeq=blkdiag(Aeq,not(act{j})); % constraints on the activation.
        %this set forces to zero those xij outside the admissibility range
        tau(j)=ceil(e(j)/p(j)); %ok
        h(j)=n-tau(j); %ok
        % costruzione matrice di shift
        for y=1:h(j)+1
            base=zeros(1,n);base(y:y+tau(j)-1)=1;
            shift{j,y}=diag(base); %ok
            shift2{j,y}=zeros(n,n);shift2{j,y}(:,y)=-base; %ok
        end
        A0=[A0 p(j)*eye(n)];
        b0=[b0;-e(j)];
        K1=[K1 K*p(j)]; %objective function: power*cost/unit
    end

    A0=[A0 zeros(size(A0))];

    % matrix shift contains occurrences of the state variables x
    for j=1:size(shift,1)
        for y=1:size(shift,2)
            if size(shift{j,y},1)==0
                shift{j,y}=zeros(n,n);
            end
        end
    end % putting zeros where there is no shift matrix
    for y=1:size(shift,2)
        A1=[A1;blkdiag(shift{:,y})];
    end
```

```
    % matrix shift2 contains occurrences of activation variables d
    for j=1:size(shift2,1)
        for y=1:size(shift2,2)
            if size(shift2{j,y},1)==0
                shift2{j,y}=zeros(n,n);
            end
        end
    end % putting zeros where there is no shift2 matrix
    for y=1:size(shift2,2)
        A2=[A2;blkdiag(shift2{:,y})];
    end

    A=-[A1 A2];
    A=[A0;A];
    b=zeros(size(shift,2)*n*m,1);
    b=[C';b];
    beq=[zeros(1,m)';ones(1,m)'];
    K1=[K1 zeros(1,m*n)];

    for j=1:m
        vect=ones(1,n);
        vect(end-tau(j)+2:end)=0;
        Aeq=blkdiag(Aeq,vect);
    end

    problem1.f=K1;
    problem1.Aineq=A;
    problem1.bineq=b;
    problem1.Aeq=Aeq;
    problem1.beq=beq;
    problem1.solver='bintprog';
    problem1.options=OPTIONS;

    tic
    [x,fval,EXITFLAG,OUTPUT]=bintprog(problem1);
    toc

    if isempty(find(x,1))
        output_sched=schedule;
    else
        SCHED=[];
        y=0;
        for j=1:m
            for i=1:n
                y=y+1;
                SCHED(j,i)=schedule(j,i+1)+(x(y)*p(j));
            end
        end
        SCHED2=schedule;
        if not(isempty(SCHED))
            % the following line updates the schedule with the tasks that
            % have been placed by the load balancer
            SCHED2(request_matrix(:,1),2:end)=SCHED;
        else
```

```
            SCHED2=schedule;
        end
        output_sched=SCHED2;
    end
end
end
```

ANNEX D

MATLAB CODE OF REQUEST GENERATOR

```
%############################################################################
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%
% The usage of any part of this code for commercial pouposes should be
% authorized by the author. Any part of this code can be used for academic
% purposes upon citation.
%############################################################################
% request(1)= appliance id {1..N}
% request(2)= appliance status {1,2,3,4,5,6}, (1=off, 2=ready, 3=run,
%                                              4=idle, 5=complete, 6=fault)
% request(3)= preemption {0,1}
% request(4)= required energy (1..E)
% request(5)= heuristic value (0,1)
% request(6)= power load {0,P}
% request(7)= execution flag {0,1}
% request(8)= arrival time {t}
% request(9)= deadline {t,t+m}
function requests = requestgen(signals, schedule)
m=6;
schedule;
request_matrix=zeros(6,9);
h=0;
for k=1:m
    for i=1:9
        h=h+1;
        request_matrix(k,i)=signals(h);
    end
end
a=diag(sum(schedule(:,2:end),2)==0);
requests=[(1:m)' a*request_matrix(:,2:end)];
end
```

ANNEX E

MATLAB CODE OF SCHEDULE MANAGER

```
%###########################################################################
% Copyright:    Giuseppe Tommaso Costanzo
% Partners:     Ecole Polytechnique de Montreal, Politecnico di Milano
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%
% The usage of any part of this code for commercial pouposes should be
% authorized by the author. Any part of this code can be used for academic
% purposes upon citation.
%###########################################################################
function [C_used,sched,count1]=schedulemanager(control,new_schedule,schedule,time,count)
m=size(schedule,1);
if isequal(control,new_schedule)
    sched_t=schedule;
else
    sched_t=new_schedule;
end
count1=((1+floor(time/10))*10);
if (count==count1)
    sched=sched_t;
else
    sched=[(1:m)' sched_t(:,3:end) zeros(m,1)];
end
C_used=sum(sched(:,2));
end
```

ANNEX F

MATLAB CODE OF DISPATCHER

```
%###########################################################################
% Copyright:    Giuseppe Tommaso Costanzo
% Partners:     Ecole Polytechnique de Montreal, Politecnico di Milano
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%
% The usage of any part of this code for commercial pouposes should be
% authorized by the author. Any part of this code can be used for academic
% purposes upon citation.
%###########################################################################
function [act,op]=dispatcher(active,schedule)
m=size(schedule,1);
open=zeros(1,m);
for k=1:m
    if schedule(k,2)~=0
        open(k)=1;
    else
        open(k)=0;
    end
end
op=open;
act=active+open;
end
```

ANNEX G

MODEL PARAMETERS INITIALIZATION

```
% parameters initialization of the DSM simulator
warning off
clc
%simulation time parameters
sim_time=100;
clock_period=0.01;
sched_timeframe=10; %how many second there are in one schedule time frame
n=10; %number of timeframes of the schedule - places to update: Cap_manager1
counter_reset=sched_timeframe/clock_period;
%appliances
m=6;                % number of appliances
act_signals_init=zeros(1,m);

dryer_deadline=40;
washm_deadline=40;
dishw_deadline=70;

C=60*ones(1,sim_time/sched_timeframe);
K=3000*ones(1,sim_time/sched_timeframe);

```